COMILLAS

UNIVERSIDAD PONTIFICIA

ICAI

Máster en ingeniería de telecomunicaciones

Proyecto de fin de máster

Identificación y recogida de objetos con un brazo robótico utilizando técnicas de reinforcement learning

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ABSTRACT

Abstract content

Thank yous

And other important information

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1. INTRODUCTION

Robotics and real life are worlds destined to meet. Today everyone has seen robots trying to behave like human beings. Many of them even look similar to a person and try to imitate the way we walk, talk or, ultimately, interact with the environment around us.

Robots, Artificial Intelligence or other concepts such as Machine Learning have crept into our lives in just a few years. In fact, until recently, only a few visionaries like Marvin Minsky or Isaac Asimov used to speak of these concepts, and it was as part of science fiction novels. Nowadays, series like Black Mirror bring this technologies closer to the general public and make us reflect on how the future could be.

However, robots, and artificial intelligence in general, are still far from the vision that is told in the novels. They are not capable of understanding the environment around them, of learning or generalizing as we humans do. Companies and researchers are working on getting better generalization of the algorithms, but the truth is that, so far, Artificial Intelligence is only able to perform specific tasks for which they are programmed.

This project is one of those cases. The goal is to control a UR3 arm robot using Artificial Intelligence in order to pick disordered objects from a box and place them in a point of delivery. This task seems trivial, because we are used to see machines performing pick and place actions in industrial processes, but in fact, these kind of processes are normally just repeating the same action or the same rule over and over again. They are able to perform this tasks because they know apriori where these objects are or how they are placed, but they are not capable of generalizing the workflow.

For instance, in Universal Robot free e-Learning course [1], they expose the following example of an industry pick and place task. In Figure 1.1 we can see how the robot is placing an object in a box located in a conveyor belt. The robot is using an infrared sensor to know that a box has arrived, and this box will always

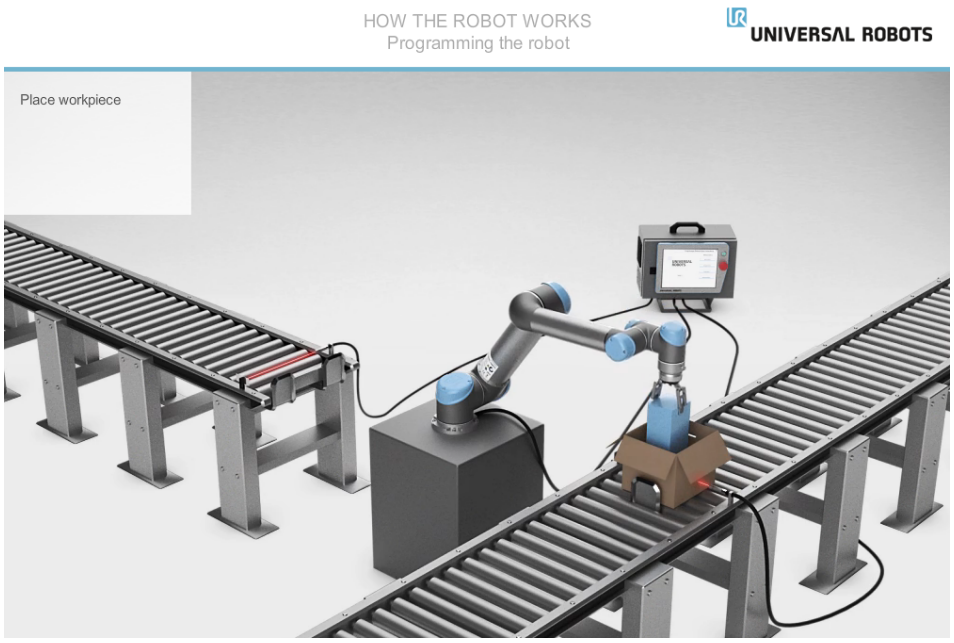


Fig. 1.1: Universal Robots Pick and Place Task

be in the same place because there is a stopper in the conveyor belt which doesn't allow the box to keep moving. On the other hand, the object is picked from the other conveyor belt using the same system to detect the arrival of a new object. The whole task is using a complex architecture, but the robot is performing the same chain of movements in a loop and the only intelligence that the robot has to have is waiting for the object and the box to come.

To achieve generalization in this project, Reinforcement Learning (RL) together with Image Recognition techniques have been used. This algorithms give the robot the ability of calculating, for each time step, the optimal action to achieve the final goal of picking all the objects from the box and placing them in the objective point. To compute this action the robot needs to gather information about the environment such as its relative position over the box or how the pieces are distributed. This information together is called state, and the robot computes each action depending on it.

To perform this project, a distributed architecture with multiple nodes has been created. Each of them takes care of a different activity. For example, some nodes are used to control the robot, others to gather information about the current state, and others are used to train the Artificial Intelligence algorithm. This architecture has been created using ROS (Robot Operative System) and contributes to the

project adding all the advantages of a microservices oriented architecture.

1.1 Project Motivation

The fourth industrial revolution is here, and it will change the way that goods are produced, raising efficiency by increasing the amount of automated processes. This will lead to a faster production and a reduction of errors, as machines have the ability to decide and act in fractions of seconds without making mistakes. Furthermore, machines can also be working 24 hours per day stopping just for maintenance checks, which would help to increase the productivity factor without increasing the expense in human resources.

We have been hearing about industry 4.0 since 2011, but the truth is that it is not a reality yet. We are just in the beginning, and it will take decades to perform such a big change in the industry. There are some factors to take in mind in order to analyse the evolution of the industry in the following years. The improvement on the telecommunications with the arrival of 5G networks, the moral dilemma of substituting workers for machines and the impact that this could have in the society or the improvement and implementation of AI technologies are just some of these factors.

We have seen a lot of Artificial Intelligence algorithms applied to the industry, but the truth is that these technologies are not fully developed yet and just big companies can afford to use them in their supply chain. Besides, there are some task that are now performed by humans and cannot be done by machines due to its complexity or its importance in the whole production chain.

The motivation of this project is to contribute to the industry change providing an open source solution to a complex problem such as disordered pick and place task. This open source solution does not currently exist in the industry and would add value being a good starting point for bigger projects in the future.

2. DESCRIPTION OF TECHNOLOGIES

Describir las tecnologías, protocolos, herramientas específicas, etc. que se vayan a tratar durante el proyecto para facilitar su lectura y comprensión. Hablar de Java no procede aquí porque todo el mundo sabe lo que es, pero si en el proyecto hablo continuamente del protocolo Baseband, debo especificar en este capítulo qué es y para qué sirve.

2.1 ROS + catkin

The first decission we had to make was about the architecture of the project. Was it a good idea to build all the project in the same computer? How should we communicate with the Robot?

We found the best solution for this questions in ROS (Robot Operative System), which is a framework for the development of software for robots that provides the functionality of an operating system in a heterogeneous cluster. ROS was originally developed in 2007 under the name switchyard by the Stanford Artificial Intelligence Laboratory to support the Stanford Artificial Intelligence Robot (STAIR) project. Since 2008, development has continued primarily at Willow Garage, a robotic research institute with more than twenty institutions collaborating on a federated development model.

ROS provides the standard services of an operating system such as hardware abstraction, low-level device control, implementation of commonly used functionality, message passing between processes, and package maintenance. It is based on

a graph architecture where the processing takes place in the nodes that can receive, send and multiplex messages from sensors, control, states, schedules and actuators, among others. The library is oriented for a UNIX system (Ubuntu (Linux)) although it is also adapting to other operating systems such as Fedora, Mac OS X, Arch, Gentoo, OpenSUSE, Slackware, Debian or Microsoft Windows, considered as 'experimental'. ROS is free software under BSD license terms. This license allows freedom for commercial and investigative use. Contributions of packages in ros-pkg are under a variety of different licenses.

All of these features made ROS ideal for the project. Specially the following ones:

- Universal Robots drivers for ROS using mooveit make it possible to controll ROS remotelly.
- ROS is a multi-node oriented framework, which allows us to take all the advantages of micro-services. We can split the software by functionallity gaining:
  - The possibility of giving more or less computation power to each functionality depending on its needs. In the project we have useed from computers with the better Nvidia Graphic card and 32 GB of RAM to other mini-computers such as a Raspberry-pi or an Arduino Card.
  - The chance of using a different environment for each functionality. Different versions of python and even different programming languages, diferent versions of libraries, diferent Operative Systems, etc.
  - Isolation of each component of the project, allowing us to develop separatly each functionality without affecting the rest of the functionalities of the project.
- It can work over an Arduino Card. It is not self sufficient, as it needs to be serial connected to a computer (Or Raspberry pi) in orther to work. We needed the arduino card in order to build our "home made" vaccuum gripper.
- It is open source and have a huge community, so we could reuse some already developed solutions such as the usb_cam package, which let us take pictures from a camara connected to another node or computer.

2.2 pytorch

PyTorch is a Python package designed to perform numerical calculations using tensor programming. It also allows its execution on GPU to speed up calculations.

Typically PyTorch is used both to replace numpy and process calculations on GPUs and for research and development in the field of machine learning, mainly focused on the development of neural networks. In this case we will use PyTorch in both the Reinforcement Learning algorithm and the image Processing.

PyTorch is a very recent library and despite this it has a large number of manuals and tutorials where to find examples. In addition to a community that grows by leaps and bounds.

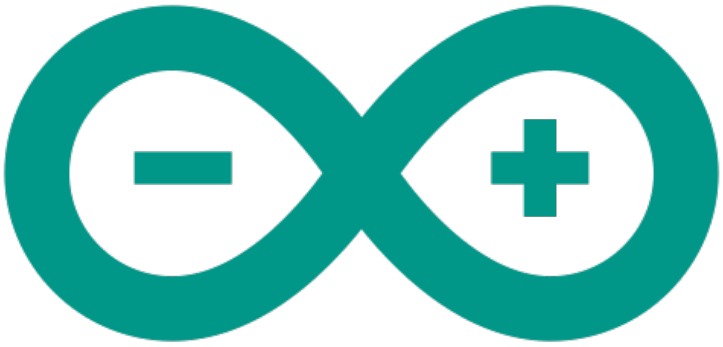
PyTorch has a very simple interface for creating neural networks despite working directly with tensors without the need for a library at a higher level such as Keras for Theano or Tensorflow.

Unlike other packages like Tensorflow, PyTorch works with dynamic graphs instead of static ones. This means that at runtime the functions can be modified and the calculation of the gradient will vary with them. On the other hand, in Tensorflow we must first define the computation graph and then use the session to calculate the results of the tensors, this makes it difficult to debug the code and makes its implementation more tedious.

PyTorch has support to run on graphics cards (GPU), it uses internally CUDA, an API that connects the CPU with the GPU that has been developed by NVIDIA.

2.3 arduino

Arduino is an open source electronics creation platform, which is based on free hardware and software, flexible and easy to use for creators and developers. This



platform allows the creation of different types of single-board microcomputers that can be used by the developer community for different types of use.

As commented before, we will use Arduino Card in order to build a Vaccuum Gripper for the Robot. It will be connected with all the other nodes using ROS Queues.

2.4 github

GitHub, Inc. is a provider of Internet hosting for software development and version control using Git. It offers the distributed version control and source code management (SCM) functionality of Git, plus its own features. It provides access control and several collaboration features such as bug tracking, feature requests, task management, continuous integration and wikis for every project. Headquartered in California, it has been a subsidiary of Microsoft since 2018.

GitHub offers its basic services free of charge. Its more advanced professional and enterprise services are commercial. Free GitHub accounts are commonly used to host open-source projects. As of January 2019, GitHub offers unlimited private repositories to all plans, including free accounts, but allowed only up to three collaborators per repository for free. Starting from April 15, 2020, the free plan allows unlimited collaborators, but restricts private repositories to 2,000 minutes

of GitHub Actions per month. As of January 2020, GitHub reports having over 40 million users and more than 190 million repositories (including at least 28 million public repositories), making it the largest host of source code in the world.

2.5 CUDA

CUDA stands for Compute Unified Device Architecture, which refers to a parallel computing platform including a compiler and a set of development tools created by nvidia that allow programmers to use a variation of the language. C programming for encoding algorithms on nvidia GPUs.

Through wrappers you can use Python, Fortran and Java instead of C / C ++.

Works on all nvidia GPUs from the G8X series onwards, including GeForce, Quadro, ION, and the Tesla line.1 nvidia claims that programs developed for the GeForce 8 series will also work without modification on all future nvidia cards, thanks to binary compatibility.

CUDA tries to exploit the advantages of GPUs over general purpose CPUs by using the parallelism offered by its multiple cores, which allow the launch of a very high number of simultaneous threads. Therefore, if an application is designed using multiple threads that perform independent tasks (which is what GPUs do when processing graphics, their natural task), a GPU will be able to offer great performance in fields that could range from computational biology to biology. crypto, for example.

The first SDK was released in February 2007 initially for Windows, Linux, and later in version 2.0 for Mac OS. It is currently offered for Windows XP / Vista /

7/8/102, for Linux 32/64 bits3 and for macOS4.

2.6 moveit

MoveIt! is open source software for ROS (Robot Operating System) which is state of the art software for mobile manipulation. In fact, we could say that MoveIt! it is becoming a de facto standard in the field of mobile robotics, as today more than 65 robots use this software, including the latest robots developed by Robotnik.

MoveIt! includes various utilities that speed up the work with robotic arms, and it helps to not be continually "reinventing the wheel", following the ROS philosophy of code reuse.

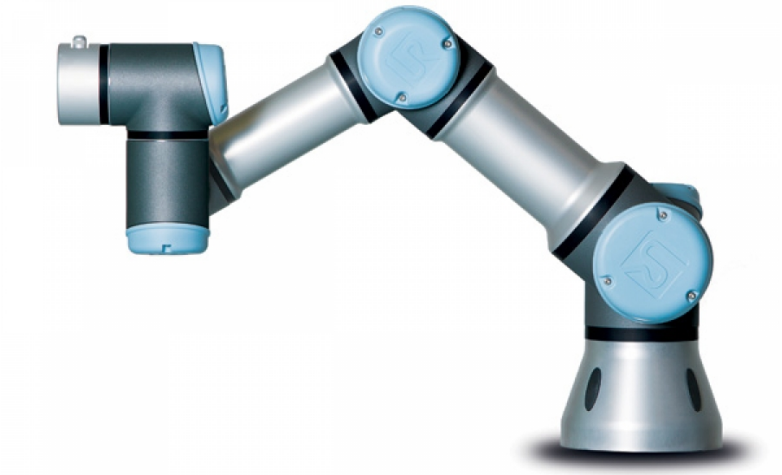
2.7 Universal Robots driver for ROS

Universal Robots have become a dominant supplier of lightweight, robotic manipulators for industry, as well as for scientific research and education. The Robot Operating System (ROS) has developed from a community-centered movement to a mature framework and quasi standard, providing a rich set of powerful tools for robot engineers and researchers, working in many different domains.

With the release of UR's new e-Series, the demand for a ROS driver that supports the new manipulators and the newest ROS releases and paradigms like ROS-control has increased further. The goal of this driver is to provide a stable and sustainable interface between UR robots and ROS that strongly benefit all parties.

2.8 UR3 robot

The UR3 Universal Robots robot is the smallest cobot of the UR series of Universal. Universal Robots' ultra flexible UR3 provides high precision for the smallest production environments.



It can modulate payloads of up to 3 kg, adding value to scientific, pharmaceutical, agricultural, electronic and technological facilities. Tasks the UR3 excels at include: mounting small objects, gluing, screwing, tool handling, welding and painting.

However, the range of movements of this robot is really limited, and it can only lift up 3 Kilograms so this robot is really good for preparing a prototype, it has the same characteristics than its big brothers, but probably it is not good enough to build a production solution.

2.9 anaconda

Anaconda is a free and open distribution of the Python and R languages, used in data science, and machine learning. This includes processing of large volumes of information, predictive analytics and scientific computations. It is aimed at simplifying the deployment and management of software packages.

The different versions of the packages are managed through the conda package management system, which makes it quite easy to install, run, and update data science and machine learning software such as Scikit-team, TensorFlow and SciPy.

The Anaconda distribution is used by 6 million users and includes more than 250 data science packages valid for Windows, Linux, and MacOS.

3. STATE OF THE ART

The pick and place task that is intended to be performed in this thesis is really useful for a lot of applications into the industrial world because it would bring a lot of flexibility for these processes. A example of this applications could be an assembly line, where robotic arms could be picking all the different pieces to assemble in the product using always the same algorithm.

Big companies are developing a lot of Artificial intelligence use cases in the industry, and they try to contribute to the AI community by publishing scientific articles on how they managed to use AI for their specific tasks. Unfortunately, although some companies have already developed their own solutions for our specific pick and place task, none of them have published a scientific article on the subject, making it difficult to study the way they have achieved it.

One of the companies that has already developed a pick and place task is the Japanese automation company Fanuc, which has developed an AI-based solution together with Preferred Networks. As commented before, they have not published any scientific article about the topic but we can see the system working in a video they have posted on YouTube [2]. That means that we have to gather all the possible information from the video, where we could find that they have not used a Reinforcement Learning algorithm but just a Deep Neural Network (DNN) with image recognition.

To train the net, they have collected "success" or "fail" labelled images by making pick actions in random places of the box. Once they gathered a big enough dataset of images, they have trained a Deep Neural Network as the one we see in Figure 3.1, where we can also see that the Neural Net has been trained to predict whether the robot is going to success in a pick action in a specific place or not. Using that net, they can make a heat map of the whole box, predicting the points of maximum probabilities of succeed. As usually, they noticed that the bigger the image dataset, the higher the success ratio. In eight hours, they reach 90% of success, which they say is bigger than the human success ratio.

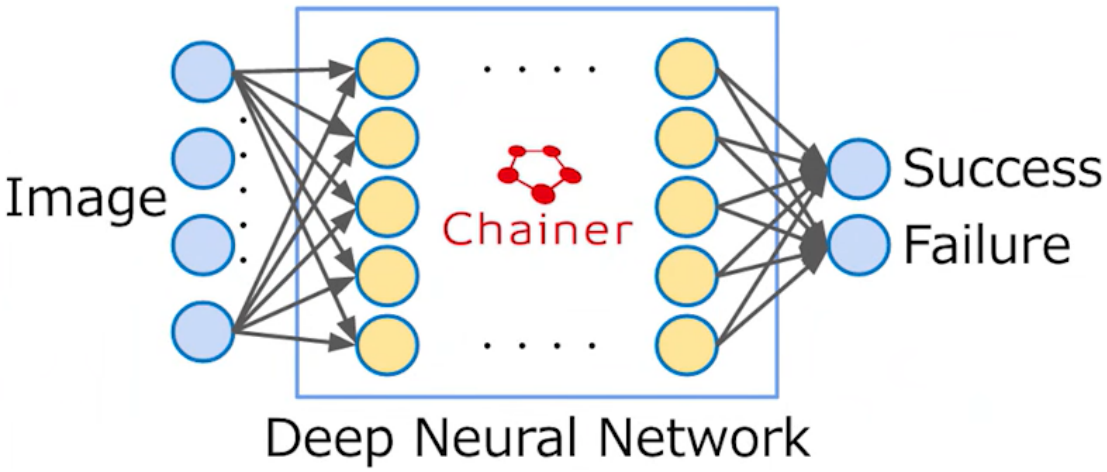


Fig. 3.1: Deep Neural Network of Fanuc solution (taken from the video)

3.0.1 Reinforcement Learning

The idea of the project is to keep using image recognition techniques but, in our case, applied to a **Reinforcement Learning** Algorithm which is an area of machine learning inspired by psychology behavioural. Its goal is to determine what actions a software agent should choose in a given environment in order to maximize some notion of "reward" or accumulated prize.

Explained easily, RL is used to make an **agent** (the robot) learn how to interact with a **environment** in order to perform a task. To achieve this, Markov Decision Process (MDP) which provides a mathematical framework for modeling decision making in situations where outcomes are partly random and partly under the control of a decision maker.

Markov Decision Process (MD)

In MDP, the environment is what we are actually trying to simulate with the MDP. The agent will interact with it to learn how to perform the task, so these are the attributes of the environment:

- **Agent:** The agent is the most important piece of the algorithm because it represents the objects that we want to become smarter.

– **Actions (A):** The agent can interact with the environment by performing a set of actions which is normally finite.

– **States (S):** Each time the agent performs an action, it moves to a new state. States are basically the set of information that differentiates the situation of the agent before and after performing an action. States can be transitional or terminal, when the agent meets the objective or when it gets to a forbidden position.

– **Rewards (R):** Each time an action is performed, the agent receives a reward. This reward can be positive, negative or null depending on the impact of the action to achieve the objective.

– **Policy (π):** The policy is used to define the optimal action for each step. It gives a punctuation for all of the actions in the current step as shown in the following formula. The agent takes the action with highest punctuation.

$$\pi(a|s) = P_r\{A_t = a|S_t = s\}$$

The MDP is divided in discrete timesteps (t), where each timestep does not have to last the same time as the previous step. Each timestep, the agent uses the policy π to decide the next action.

Once the action is taken:

– The environment transits to th next state: $\boldsymbol{S_t = S_{t+1}}$.

– Environment produces a new reward, which can be represented with the following formula:

$$\boldsymbol{P(s', r, s, a) = P_r\{S_{t+1} = s', R_t = r, S_t = s, A_t = a\}}$$

Agent's performance is calculated in terms of its future accumulated rewards known as return. This is called **expected return** an is calculated as shown in the formula below, where γ is the discount factor, and is used to give a bigger value to the closest steps.

$$G_t = \sum_{k=t} \gamma^{k-t} \cdot R_{k+1} \ \forall \ \gamma \in [0, 1]$$

Q-Learning

Now that we know all these concepts, we have to learn what Reinforcement Learning Algorithms do to learn. Basically, **the goal of the agent is to find a policy that maximizes the expected return** . This can be done using different strategies as:

- **Q-Learning:** Estimating action values using Q Tables or other methods
- **TRPO:** Parametrizing the policy and optimizing its parameters

Basic Q-Learning is based on the assumption that both actions and states are limited and that the same action in the same state always drives to the same new state. Having this in mind, Q-learning algorithms build two matrices of shape **length(actions) x length(states)** as shown in the Figure 3.2.

In these two matrices, Q-Learning algorithm stores in the R matrix the reward for the pair of action-state while in the Q matrix they store cumulated reward for this same pair. The Q matrix is the one used to decide which action to perform in each state and R matrix the one used to calculate the reward of each action.

However, for the aim of this project, the states of the agent can be different in each timestep. The state would actually be partially formed by images, so the number of states can be infinite. We need a more complex version of Reinforcement Learning.

3.0.2 Deep Reinforcement Learning

The approach of mixing both image recognition and RL is called Deep Q Learning (DQN) or Double Deep Q Learning (DDQN) depending on the implementation and uses Neural Networks in two different stages of the algorithm. Firstly, a Convolutional Neural Network (CNN) is used to extract image features, and then, a Deep Neural Network (DNN) is used to calculate the q value of each independent action and select the next one using these values.

DQL was proposed in 2012, and, since then, it has been used for a lot of different purposes. For example, Guillaume Lample and Devendra Singh Chaplot demonstrated back in 2017 that a RL agent could play FPS Games using as inputs just game scores and pixels from the screen [3]. Another really interesting example

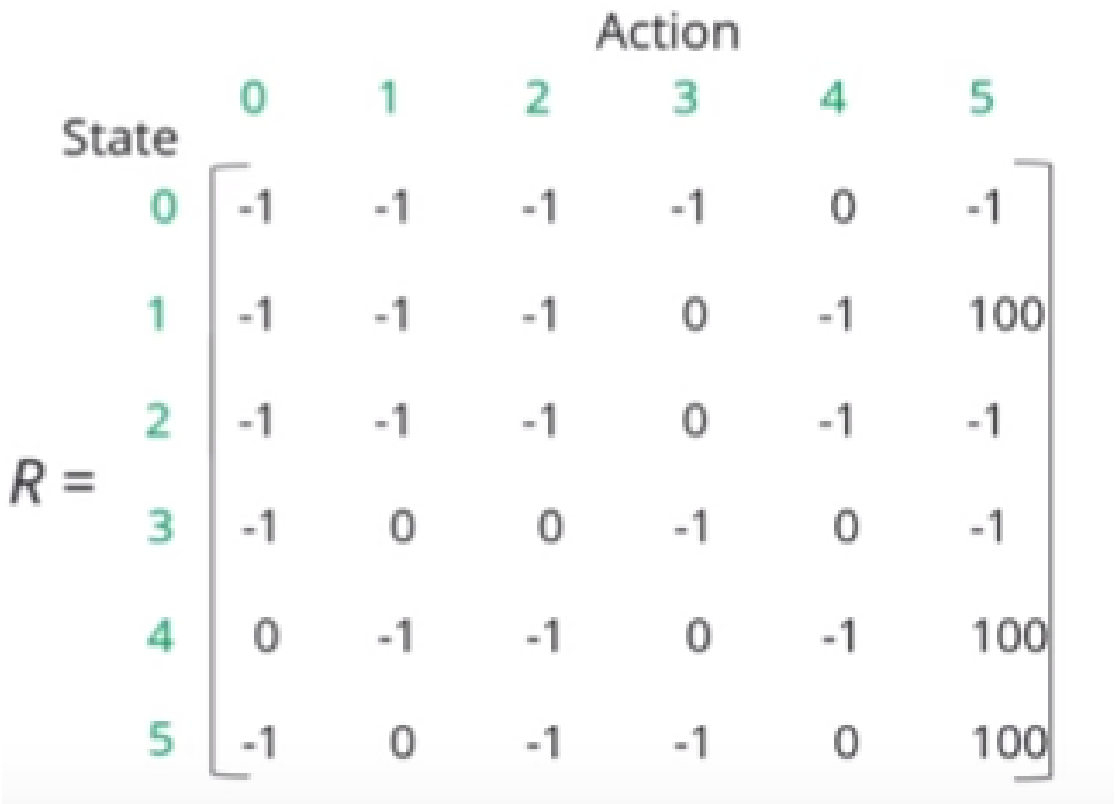


Fig. 3.2: Reward and Q Matrix shape in Basic Reinforcement Learning

is this robot [4], which is capable of moving around a house looking for an objective and avoiding obstacles using DDQL.

A good resource to understand how Reinforcement Learning really works is Deeplizard's tutorial [5]. In this tutorial they explain different versions of the algorithm and how to implement them in python to solve different OpenAI gym environments [6].

Deep Reinforcement Learning is though an union between RL and image recognition, but let's see how it actually works. The main idea is to replace the Q-table that we saw before for a Dense Neural Network that uses as input another Neural Network, a Convolutional Neural Network (CNN). The full algorithm would have as many outputs as allowed actions. Therefore, simplifying, these outputs re equivalent to the q-values saw before and so we will call them. To see it graph-

ically, when the agent wanted to take an action, he would pass the state image through the Neural network represented in Figure 3.3 and would take the action with higher q-value.

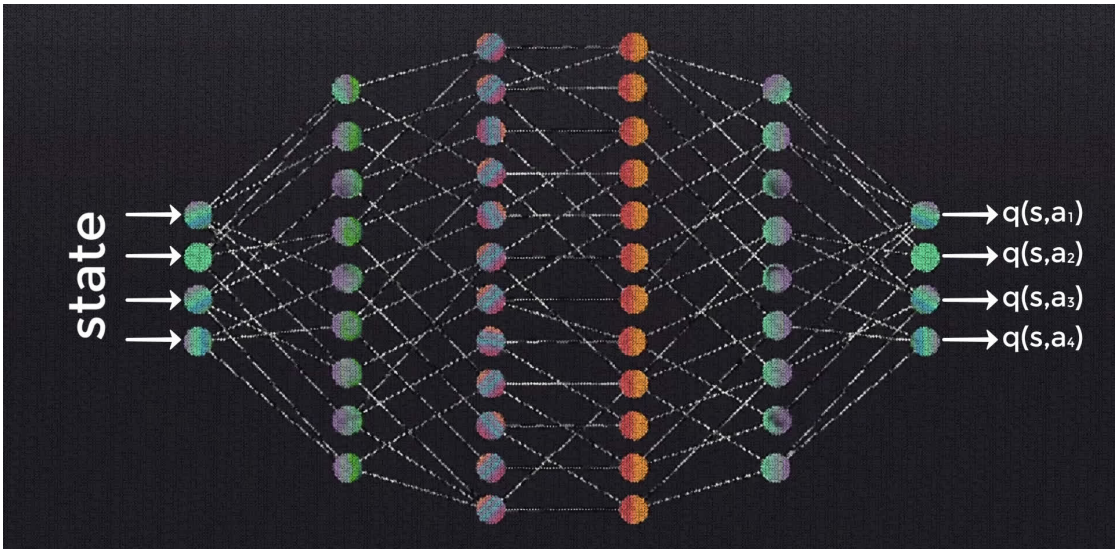


Fig. 3.3: Deep Q Learning Representation with 4 outputs

When I said "simplifying" in the previous paragraph, I meant "simplifying a lot" in the next paragraphs I will explain all the intermediate steps in the algorithm and why they are important:

- Episodes and Steps
- Exploration vs Exploitation trade-off
- Replay Memory
- Bellman's Equation
- Target and Policy Networks

Episodes and Steps

RL training is divided in Episodes. One Episode is the sequence of actions needed to reach a terminal State. Each time the agent reaches a terminal state, an episode is ended, and a new one is started.

On the other hand, steps represents every time that a new action is taken, so the number of steps taken by the agent during training is infinite. Later on, we will use as metric of performance the number of steps per episode, as they must decrease during the training.

Exploration vs Exploitation trade-off

In Reinforcement Learning there are two important concepts that are **Explore** and **Exploit**. To explore is basically gather new information about the environment and to exploit is to make the best decision with the information that we already have.

In Deep Reinforcement Learning, the agent exploit the information gathered by using the pre-trained Neural Network to decide next action. On the other hand, the agent explore the environment by deciding next action randomly. We use exploration mainly in the beginning of the training because we want the agent to gather as much information of the environment as possible before starting training.

When the agent uses exploitation, it is also gathering information about the environment. However, we could not let the agent explore this way because during the exploration phase we want all the actions to be performed with the same probability and neural network bias can cause some actions to be performed much more than others.

So, how do we decide when the agent must explore or exploit? To decide it we can use multiple techniques, but the most common one is the Epsilon-Greedy Strategy. This strategy basically consist on setting a probability of exploring and keep decreasing it slowly during the training. It works this way:

1. **We set the initial exploring probability** (ϵ)
2. **We set the per-step epsilon decay,** (ϵ_decay)
3. **For each step:**
    (a) **With probability** $p = \epsilon$**, the agent explores the environment (takes a random action). If not, it exploit the information by deciding the action using the NN.**

(b) **Whether the agent has explore or not, we decrease the probability of exploring the environment in the next step ($\epsilon = \epsilon - \epsilon\_decay$)**

Using this strategy, the agent will rather explore or exploit the environment during the training. In the first steps the probability of a random action (exploring) will be much hihger than in the last steps of the algorithm. This probability will keep decreasing during the training, until it reaches the minimum exploring rate, which is normally set to 10

Replay Memory

Every time that the agent performs an action, either by exploring or exploiting, the agent lives an experience. For the purpose of training the algorithm, we will store all these experiences.

Experiences are formed by the initial state, the action taken, the state reached (final state) and the reward gotten and they are stored in the Replay Memory. Then, every time that an action is taken, the algorithm is trained following this steps:

1. Replay Memory checks if the number of experiences is higher than the batch size
2. If there are enough experiences:
   (a) Replay Memory supplies a random set of experiences of size=batch_size.
   (b) With this set of experiences, the target network is trained.

Optimizing Replay Memory can be a challenge, because, if we are using a Graphic Card in the training, we would be storing all the experiences in its memory. But, why do we need to store all the experiences? We could also be using the last N experiences to train the network and it would be a less memory-consumption demanding solution.

The answer to this question is that Reinforcement Learning Networks converge really slowly and variance between consecutive steps is really low. Using consecutive experiences to train the network would result though in a slower and biased learning. Besides, this way of working is better for learning real-world experience,

where there are infinite different states, as the experience gained in previous steps will be used multiple times later to train the network.

Bellman's Equation

As commented before, Deep Reinforcement Learning uses Neural Networks to compute the q-values of each action. The optimal value of these q-values is represented by the Bellman's Equation and is shown below:

$$q_*(s,a) = E[R_t + \gamma max(q_*(s',a')]$$

As we can see in the equation, the optimal value depends in both the reward of the action taken and the maximum optimal q-value of the next action. In real life it is impossible to compute this value, because we would be an infinite loop. However, as the most important parameter of the formula is the expected reward ($q_*(s',a')$ is multiplied by the discount factor γ), we can simply use the next action q-value and it will be a good approximation. The formula would stay as follows:

$$q_*(s,a) = E[R_t + \gamma max(q(s',a')]$$

With this new formula we will be able to compute the optimal q-value for each experience stored in the Replay Memory (initial state, action, final state and reward). It is important to have in mind for this process that the optimal q-value can only be computed if the action has actually been taken, because we don't know the Reward of non taken actions. But, anyway, why do we need to compute the optimal q-value?

To answer this question, lets take a look to the training process of the neural network:

1. the agent decide which action to take using the policy-network. (action with highest q-value)
2. The agent takes the action and receives a reward from the environment
3. The agent stores all the experience in the Replay Memory

4. The training process is started:

   (a) A random batch of experiences is taken from the Replay Memory

   (b) For all these experiences, its optimal q-value is calculates using the modified Bellman's Equation and target-network

   (c) For all these experiences, the actual q-value is calculated using the policy-network

   (d) For all these experiences, the loss is calculated as the difference of both values

   (e) We use the Neural network optimizer to back-propagate the loss to all the weights

So, to answer the previous question, we need to compute the **optimal q-values in order to calculate the loss** of the neural network for each action taken and train, though, the algorithm.

Retaking here the question answered before about why we needed Replay Memory module, one important reason is that one action taken in the initial steps of the training will affect differently to the neural network in this moment than later, when the network is already trained, and its q-value is though more similar to the optimal q-value. Replay Memory technique allow us to use this information gathered in any step of the training, during a step where the network is more trained.

Target and Policy Networks

In the previous step, we talk about two different networks: policy and target. The target network comes to solve a stability problem of the DRL training. In the next paragraphs I will explain the problem and how target network can help to solve it.

Having in mind the way we calculate the loss of the neural network in the previous section we can realize that we have to pass information through the network twice. Just to remember:

$$loss = R_t + \gamma max(q(s_{t+1}, a_{t+1})) - q(s_t, a_t)$$

As a spoiler, I can say that $q(s_{t+1}$ and $q(s_t, a_t)$ will not be calculated with the same network. But.. why?

Imagine that we have an experience, which is composed of an initial state, an action that has been taken, the state reached with this action and a reward. Remembering previous section, the loss of the neural network is calculated as the difference between the q-value of the initial state and the action taken and the optimal q-value of the expected cumulative reward (or target value) of the action.

Q-values are calculated using the states as input of Neural Networks. Let's see what could happen if we calculated both of the values with the same network. In this case, once we had the loss calculated, we would use back-propagation to adapt the weights of the Neural Network and make the q-value of the initial state more similar to the target q-value.

The problem here comes because as both q-values are using the same Neural network to be calculated, when we change the weights to move the initial q-value to one direction, the target q-value is moving in the same direction, so we have not reduce the distance between the two values. It is basically like a dog chasing its tail.

To solve this problem we introduce the target-network. This network is basically a frozen clone of the policy network that we only use to calculate the target value of each action. This way, when we gain stability during the training of the RL Algorithm. The target-network is updated periodically after a certain amount of steps, so is always updated.

DQL Training

During the previous sections I have been explaining a lot of concepts about Deep Reinforcement Learning Training. I have explained them and how they affect the training. It is a really complex process so probably a sum-up will help understanding it.

The training basically uses the following schema:

- Initialize replay memory capacity.
- Initialize the policy network with random weights.
- Clone the policy network, and call it the target network.

- For each episode:
  - Initialize the starting state.
  - For each time step:
    - Select an action via exploration or exploitation
    - Execute selected action and observe reward and next state.
    - Store experience in replay memory.
    - Sample random batch from replay memory.
    - Preprocess states from batch.
    - Pass batch of preprocessed states to policy network.
    - NN training. Weight back-propagation:
      - Calculate loss between output Q-values and target Q-values.
      - Using both the target and the policy networks to increase stability.
      - Gradient descent updates weights in the policy network to minimize loss.
  - After X time steps or episodes, weights in the target network are updated to the weights in the policy network.

This training can also be explained with Figure 3.4, where the Pool is the Replay Memory that stores the sample (experiences) from real interaction with the environment and feeds the training node of random sample of experiences.

Then, we can see that we use the Q-Network (policy network) to predict actions, but also to calculate the q-value of Replay Memory's batch. Then, we use the target network to predict action-value of state s1 with the predicted action in Q estimation Network, andthis network is updated in a low rate.

Finally, the action taken in the Dynamic Environment can be predicted by the Neural Network or Randomly chosen (Stochastic search). This is the way of representing epsiolon-Greedy Strategy.

3.0.3 Problems of Deep Reinforcement Learning in Real-world

Real-world problems introduces some challenges that we will have to manage. In march 2018, A. Rupam Mahmood, Dmytro Korenkevych, Brent J. Komer,

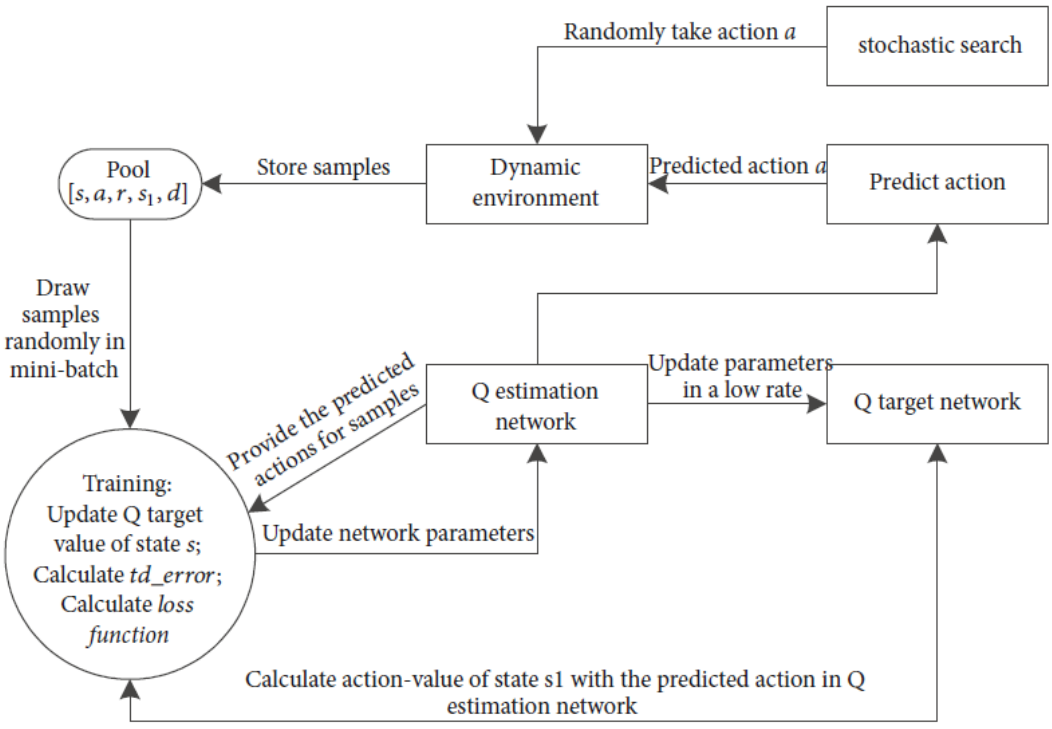


Fig. 3.4: Reinforcement Learning Training Summary

and James Bergstra explained the problems they found while implementing a RL algorithm in a UR5 robotic arm [7].

Some of the problems they found were the following:

- Slow rate of data-collection, as movements in the real robot are slower than in a simulated environment.
- Partial observability. Sensors cannot retrieve all the information about the environment.
- Noisy sensors will provide inaccurate information.
- Safety of the robot and its surroundings have to be taken in mind.
- Fragility of robot components.
- Delay between an action is requested and the time it is actually performed can affect the training.
- Preparing the robot is a really difficult task:
  - Controlling the robot.
  - Define all aspects of the environment.
  - Difficulties for obtaining random and independent state when episode ends.

Another problem that can be found in our project is that, as objects are randomly placed, the environment that the agent will have to face will be completely different each time. In fact, the robot can interact with the environment, as it can move the pieces trying to pick them, so we are facing a dynamic environment RL problem. A good example of a dynamic environment problem is the path planning of a self driven car, where each time the agent takes an action the environment will change and, furthermore, obstacles do not have to be static, but they can also move.

There are multiple examples of articles on this topic, such as the one Xiaoyun Lei, Zhian Zhang, and Peifang Dong published in September 2018 using a DDQN approach to solve it [8]. However, there are other solutions as the one proposed by Marco A. Wiering [9], where he introduces some prior knowledge to the model in order to facilitate the learning. His algorithm had problems generalizing the

environment, so he introduced some prior information about the model together with a Model-based RL. This made the algorithm more capable to learn without loosing a lot of trainable capability.

4. DEFINITION OF THE PROJECT

4.1 Motivation

The project motivation is the natural continuation of a previous project performed at ICAM University. This project was part of the assembly line of a car manufacturing process and its objective was to pick some specific plastic pieces and place them into the product. To achieve this, the system used opencv image processing, so it was recognising a specific shape given apriori.

This project was totally functional and the robot could perform the task with a high successful rate. However, the lack of generalization of the system makes it hard to introduce changes as using it for another part of the assembly line. Each time that this happened someone would have to introduce the shape of the pieces to the system and to calibrate the camera to the new environment.

The motivation of the project is to create from scratch a new solution for performing the picking of the pieces. This time, the project will not be sponsored by any company, so there will be less resources to use.

With this new approach, the idea is to use all the knowledge of previous documented projects on Artificial Intelligence in the industry and make a little contribution to the huge advance of industry 4.0. In fact, the idea is to make the project completely replicable so that anyone could use this project as a starting point for new applications.

4.2 Objectives

This project is a really big project that is impossible to face entirely by two people in 5 months. Having this in mind, the objectives have to be ambitious, but realistic, and that is the reason why we cannot expect to build a product that can be sold,

or a final version of a system. In a company, this would be the work of a big development team, so we cannot be compared to them.

The objectives are:

- Implement a bin picking simple solution. A basic one, without Artificial Intelligence.
- Improve the performance using RL and Image Recognition.
- Study the usage of new technologies to add information to the system.
- Create a functional system that can be continued and that delivers the first results.
- The system should empty the box with a rhythm of 2 pieces per minute.

4.3 Methodology

This project will be performed using an agile methodology, which is one of the simplest and effective processes to turn a vision for a business need into software solutions. Agile is a term used to describe software development approaches that employ continual planning, learning, improvement, team collaboration, evolutionary development, and early delivery. It encourages flexible responses to change [10].

In the case of this project, the team is just formed by two workers and a project manager. This make necessary to make some changes to the typical agile methodology. For example, daily meetings are substituted by constant communication between both workers and weekly meetings with the project director. With this approach, all the members of the project are updated about how it is going and have clear objectives.

Likewise, the methodology of this project is based in three fundamental principles as it is shown in Figure 4.1. The first two principles are highly related, as the project is iterative because it is experimental. That means that the way of working is perform little sprints with new functionalities, test them (experimental) and, depending on the results, define the new sprint, execute it and test again (iterative). Besides, the project is also incremental because the idea is starting implementing the simplest possible solution and keep adding new improvements to it in a iterative loop until the optimal configuration is reached.

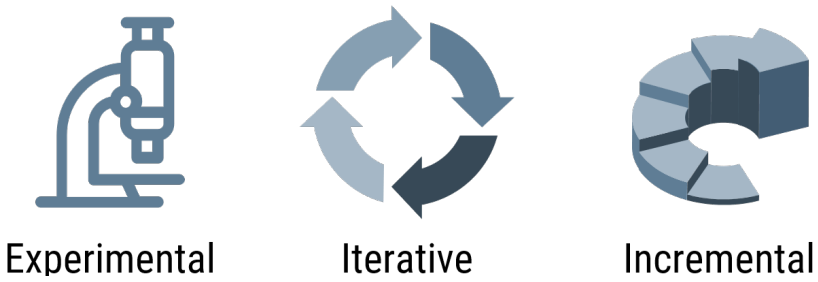


Fig. 4.1: Methodology

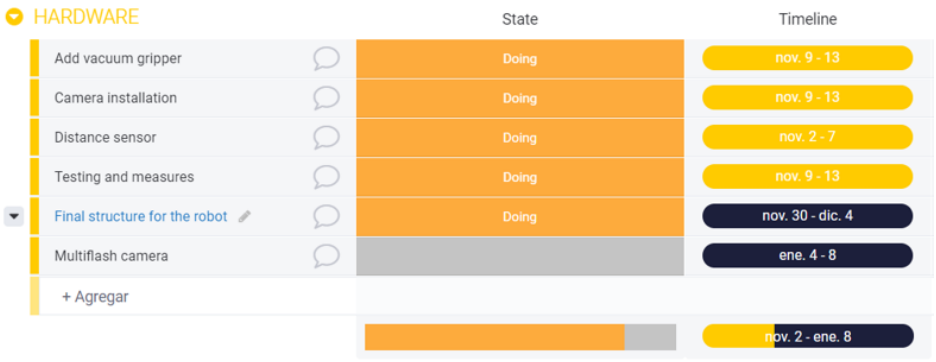


Fig. 4.2: Chronograph of the Hardward implementation

4.4 Planning and budget

Regarding the planning, there are some really important functionalities that have been defined since the beginning of the project, as they are needed. These functionalities are split in three different groups: Hardware implementation, Artificial Intelligence Implementation and Robot controller implementation. The tasks related to these three groups are shown in Figure 4.2, Figure 4.3 and Figure 4.4.

4.4.1 Budget

The budget of the project was really limited because it was not sponsored by any company. The cost was mainly due to hardware acquisition. For example, the gripper was design and built by us in order to save thousands of euros.

In the following table we can see the detailed budget of all the project:

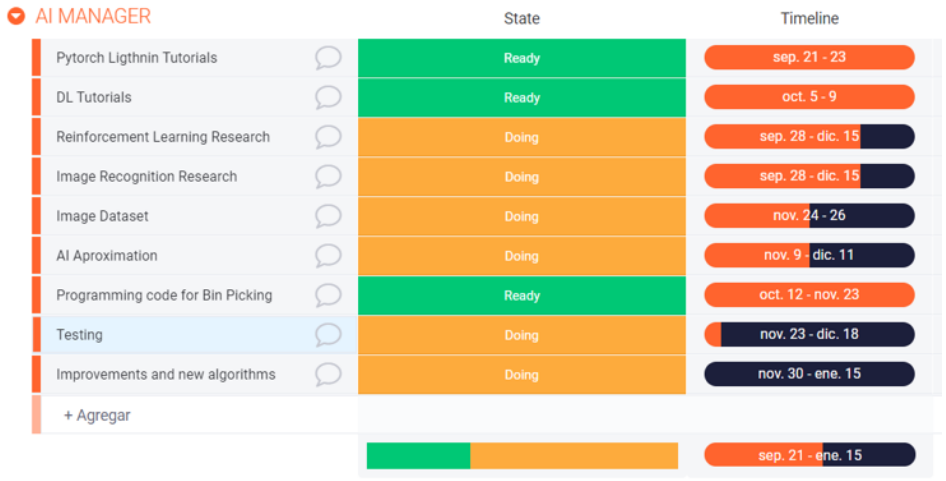


Fig. 4.3: Chronograph of the Hardward implementation

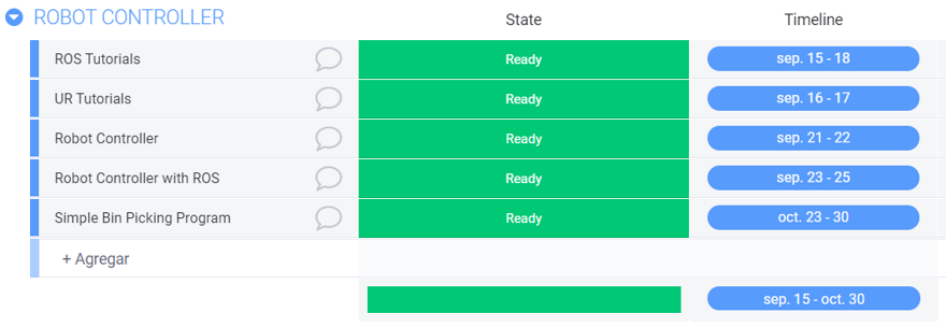


Fig. 4.4: Planning of the Robot Controller implementation

ITEM	QUANTITY	PRICE
Nvidia Geoforce GTX	2	395,88
Vacuum Gripper	1	53,50
Raspberry Pi4	1	59,05
Electronic Parts	(Sensors, transistors..)	30
Arduino	1	22,64
HDMI-¿VGA	2	63,31
QWERTY keyboards	2	36,85
	Total	661,23

Tab. 4.1: Project's Budget

5. DEVELOPED SYSTEM

In previous sections of this documents, I have explained the main idea of the project, and what technologies are going to be used to develop a fully functional system. Just to remember, the objective of the project is to perform a Pick and Place task using a Universal Robots' UR3 robotical arm.

The objects have to be taken from a box (Environment Box) and placed in another box (Place box). The pieces had to be something light due to the limitations of the UR3 robot that we commented before. As there wasn't any sponsor for the project we could decide the shape of the pieces, and we decided to use 5 cm size wooden squares as the ones showed in Figure 5.1.

Fig. 5.1: Wooden Pieces used in the project

5.1 Hardware Architecture

In order to make this system work, we need a really complex architecture that can be split in three different categories. These categories are:

- Environment
- sensorimotor devices
- Computational devices

To understand it better, we are going to use Figure 5.2 and Figure 5.3, which are labeled pictures of the architecture, where we are going to be able to see how the components of the architecture are like.

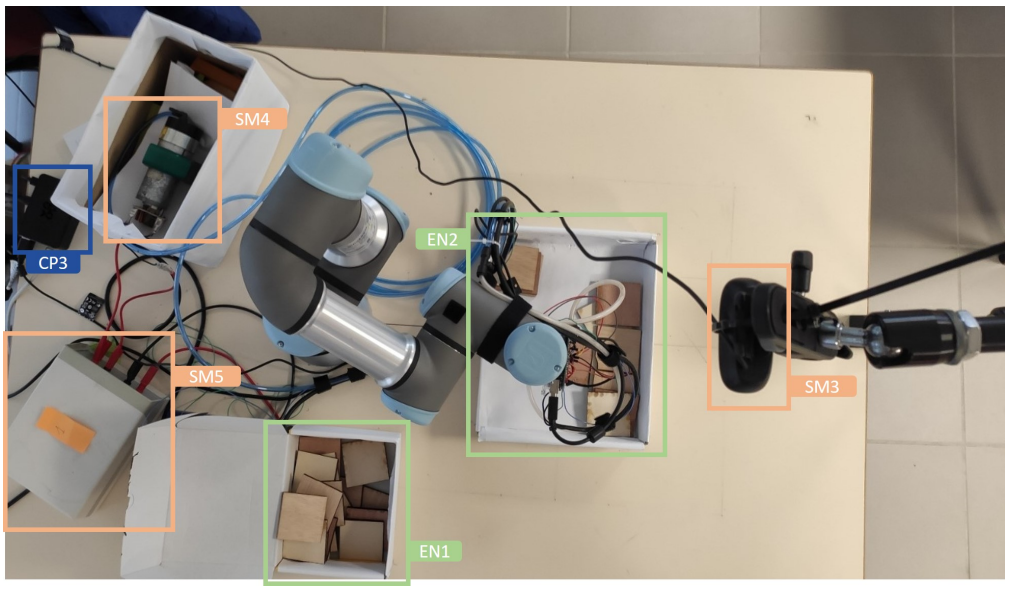


Fig. 5.2: Labelled picture of the Architecture I

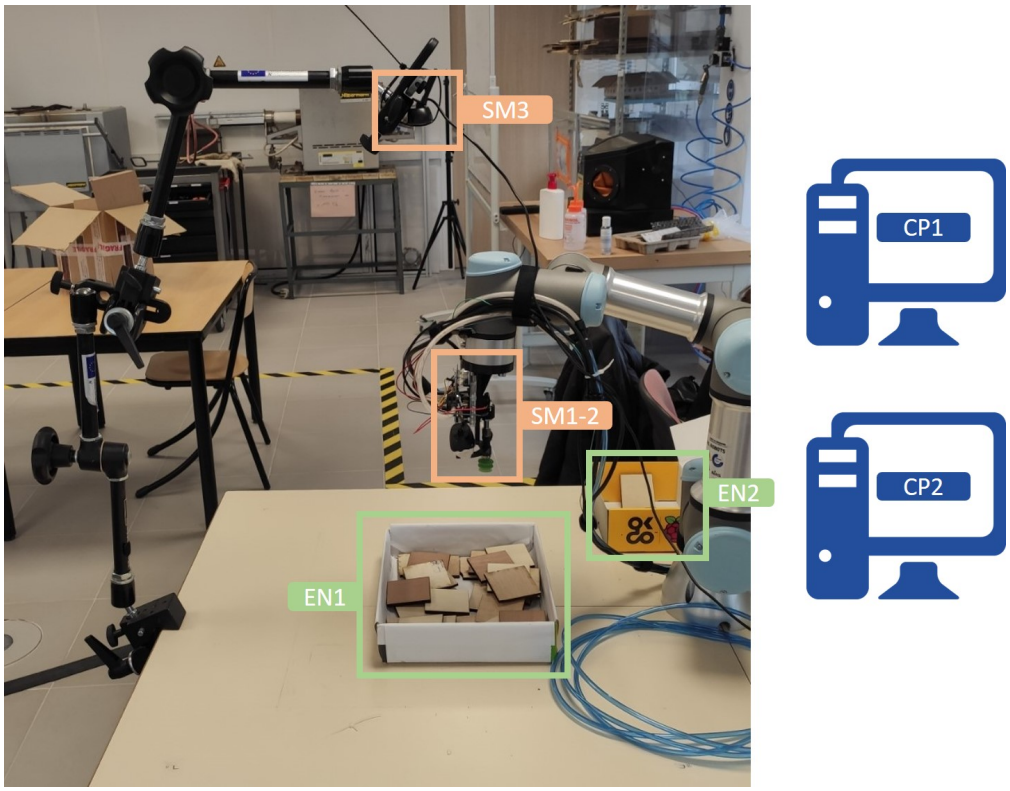


Fig. 5.3: Labelled picture of the Architecture II

In the pictures we can see multiple elements tagged with different colours and labels. Each colour represents a category.

The environment elements, that can be found in green, and labelled with EN, are basically all the things that the robot will have to interact with. The sensorimotor elements, that can be found in orange and with the label SM, are all the elements needed to allow the robot interact with the environment. And finally, in blue and with label CP, we can find the computational elements, which are the ones used to receive all the sensor information, decide which movement to do, and communicate with the robot and the gripper for them to actually perform these actions.

But, what are all these elements? Let's explain them:

– **Environment**: We can see this elements in both images, from different perspective.

  - **EN1**: The Environment box where the agent has to take the pieces
  - **EN2**: The box where the agent has to place the pieces

- **Sensorimotor devices** Ones are showed in one image, and others in the other.
  - **SM1**: This is the Onboard camera, used for the agent to decide which action to take. It is attached to the gripper, so in the picture they are shown together.
  - **SM2**: Together with the camera, we can see the "Home made" gripper used to pick the pieces.
  - **SM3**: the upper camera, where the agent can pick a global picture of the environment. This picture will be important, but we will explain it later.
  - **SM4**: the pump of the Gripper.
  - **SM5**: Both 12V and 24V power adaptor used to feed the pump and some sensors.
- **Computational devices**. In the picture we cannot see all the computer used in the project, but there are 2 icons used to represent them.
  - **CP1**: This is the ROS Master Node. All of the nodes of the system will be connected to this node. Besides being the master node, robot_controller node and Universal Robots driver will also bo running in this computer.
  - **CP2**: This computer is a really powerful one, with one of the bes graphical cards in the market an 32 GB of RAM. It will be used to train the algorithm, running the ai_manager node.
  - **CP3**: This mini-computer can be seen in one of the pictures and its a Raspberry-pi. This computer will be used as a bridge form the arduino card of the gripper and the ROS master node. The cameras will also be attached to the Raspberry-pi.

5.2 Logical Architecture

Once we have seen the physical architecture of the project, let's see how the Software architecture is. The Logical architecture will use all the elements commented

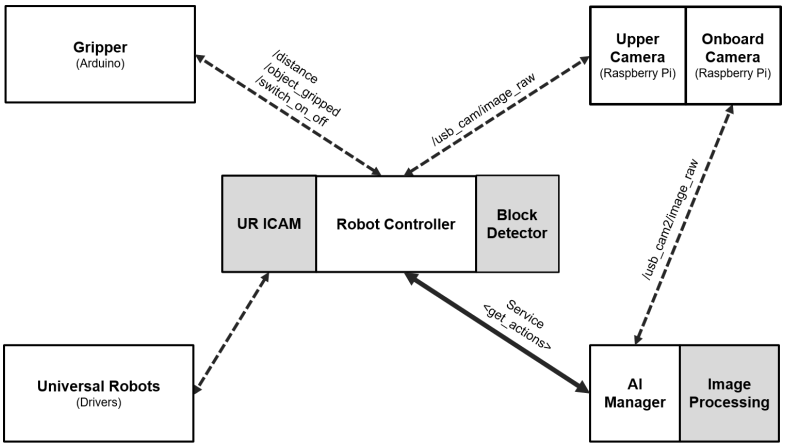


Fig. 5.4: Logical Architecture of the project

on the previous section, and they will work together using ROS (Robot Operative System).

In Figure 5.4 we can see the logical architecture of the application, which is composed of 6 nodes communicating one with each other. We can see that the communication topics are written in the figure and that there are some squares attached one to another, and some of them are grey. All the white squares are ROS nodes, while grey ones are separate pieces of code that the nodes are using, but they are not ROS nodes by themselves. On the other hand, both camera nodes that are together in the upper right corner are two independent nodes, but using the same code to send the cameras images.

To explain briefly what every node does, probably it is easier going step by step from the simplest architecture to the final one, so that we see what every node is doing.

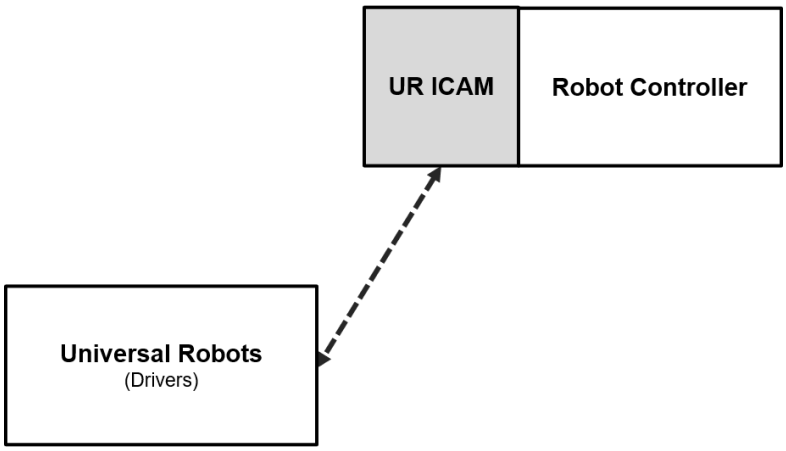


Fig. 5.5: From the simplest to the final Architecture I

In Figure 5.5, there are only three components. However, Both Universal Robots Drivers and UR ICAM were not developed by us and are like black-boxes for us. That is the reason why there are no ROS topics written in the communication the figure.

Universal Robot Drivers is the one that actually communicates with the robot, and provides all the basic tools needed to control it remotely. On the other side, UR ICAM node is a node developed in the university, and it provides us some methods to control easier the robot. These methods are a personalization of the ones provided by MoveIt library, and they make us possible to go to some angular coordinates of the robot without calculating the optimal path to reach this position, or the same thing with some cartesian coordinates.

Finally, the Robot Controller node is the one that actually is communicating with all the othe nodes of the architecture. All the actions that the robot will be able to perform are here, so just with Robot Controller node we could almost be able to implement a silly random agent to perform a pick and place task.

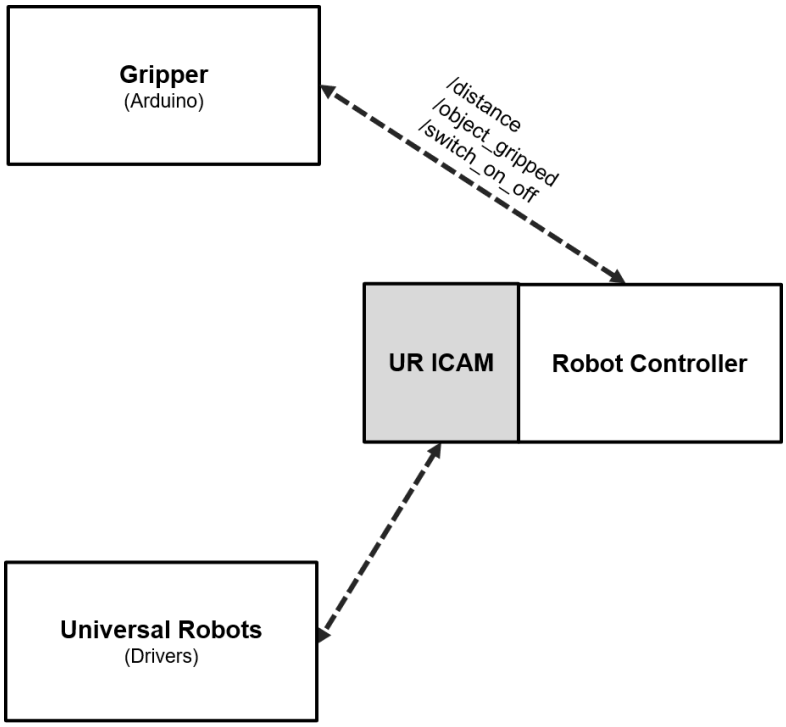


Fig. 5.6: From the simplest to the final Architecture II

I said almost, because to perform a pick and place task we also need the gripper node, as we can see in Figure 5.6. This node is running in an ardunio carda communicates by serial port with a Raspberry Pi, which is also connected with the master node. The gripper node uses 3 different topics to communicate with Robot Controller:

- ***\distance:*** The gripper is publishing continuously if the gripper is being pushed up or not. Robot Controller wants this information to know when to stop during the pick movement. The Robot basically goes down while ***\distance*** are "False" and stops when they are "True".
- ***\switch_on_off:*** The gripper listens to this topic. When it receives a "True" message it switch the gripper on, and when it receives a "False" message it switch the gripper off.
- ***\object_gripped:*** The gripper is publishing continuously if there is an object gripped or not. Robot Controller use this information during the pick action. When this action is finished, robot controller checks if an object has

been picked or not by reading from this topic. If an object has been picked it goes to the box to place the object and, if not, it just finishes the pick action and request AI Manager for a new action.

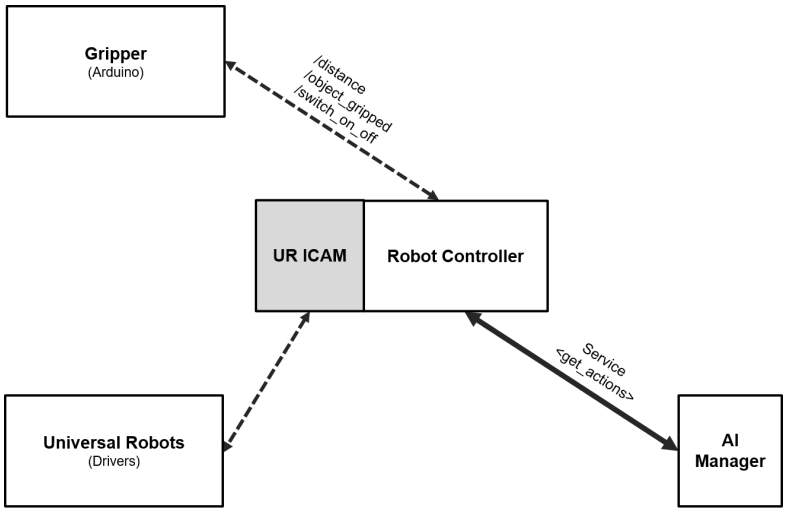


Fig. 5.7: From the simplest to the final Architecture III

The next step in our trip would be adding the AI Manager Node. This Node is the one who decides which action to perform in each time step. It receives the Coordinate, request an image of the environment (Which in this step is still simulated) and trains a Reinforcement Learning Algorithm to decide which action to perform in each step.

As we can see in the Figure 5.7, the arrow representing the communication between Robot Controller and AI Manager is the only continuous line. This is because the communication method is different, in this case we are using ROS Services instead of publishing the messages in topics.

In ROS, the most common way of communicating is using ROS Messages. ROS Messages are simple data structures that are send to a topic, which is basically a queue stored in the Master node. Then, other nodes can be subscribed to this topics so every time that they are free, they ask the master node about the unread messages in the topic. This is called asynchronous communication and, it is probably the best way of sending messages between nodes, because it allows the receiver to adapt its computational needs to the message load received from the topics.

However, in this case asynchronous communication was not possible, because ROS Messages does not ensure the delivery. This was a problem because the Robot Controller could request an action to the AI Manager, and the second one could not receive the message. This is not a problem in this direction because we can solve it by putting a timeout in Robot Controller, and it could make a new request after x time.

Anyway, this could not be a solution because we need to avoid the AI Manager node to receive the same request twice. This is needed because every time that the AI Manager receives a new action, a new step of the training is performed: A reward is given, random probability decreases, Experience is saved, etc.

ROS Services is the way of performing synchronous communication in ROS, and it ensures that every message is delivered once and only once. AI Manager is though a resting node that does nothing until the Robot Controller nod request an action. It then start calculating the action, trains the net and return the selected action.

get_actions services is defined by two structures:

- Request structure:
  - **x_coordinate:** X coordinate of the robot used to calculate the reward and training the robot.
  - **y_coordinate:** X coordinate of the robot used to calculate the reward and training the robot.
  - **object_gripped:** Boolean telling whether the robot has an object gripped or not. It is used to calculate the reward of pick actions.
- Response structure:
  - String telling the action selected

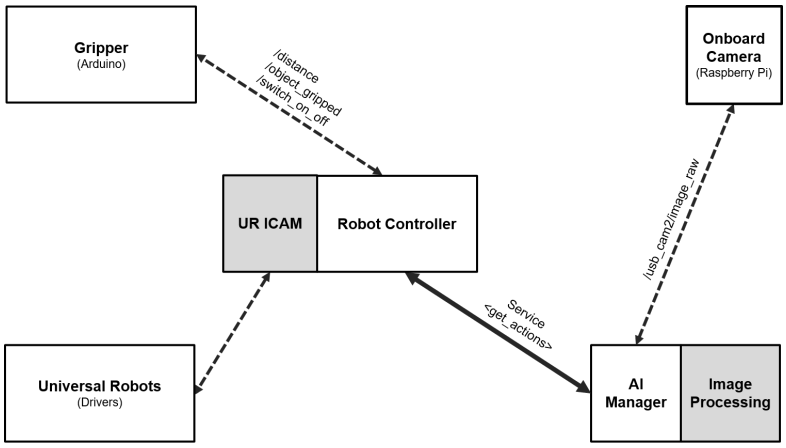


Fig. 5.8: From the simplest to the final Architecture IV

We commented before that AI Manager needs to gather a state image in order to start the training. To gather this image, it just requests a message from ***−usb_cam−image_raw*** topic. Messages of this topic are published by Onboard Camera node, which is basically an instance of usb_cam node that publishes with a 30 fps rate the images of the Onboard camera of the robot.

But once the Ai Manager has the image, it has to process it and extract its features, and Ai Manager will do it using the models in Image Processing. We will talk deeply about this later, but it basically means to make some transformation to the image (Changing its shape, color, rotation, etc.) and pass it through a pre-trained Convolutional Neural Network in order to extract some features. This features are actually the ones that will be passed through the Reinforcement Learning Neural Network and the ones that will be stored in the Replay Memory.

Finally, the last two nodes that we have not commented from Figure 5.4 are the Block Detector and the Upper Camera Node. Block Detector is a piece of code used by Robot Controller when it is performing a place action. In this moment, the robot is out of the box and has to decide the initial coordinates of the next episode. The upper camera has, though, a full view of the environment, so the Robot Controller takes the environment picture from the topic ***−usb_cam2−image_raw*** where the Upper Camera node is publishing the images of the upper camera. Then it passes the image to the Block Detector which finally calculates the optimal point of return, avoiding the places of the box where there are no pieces.

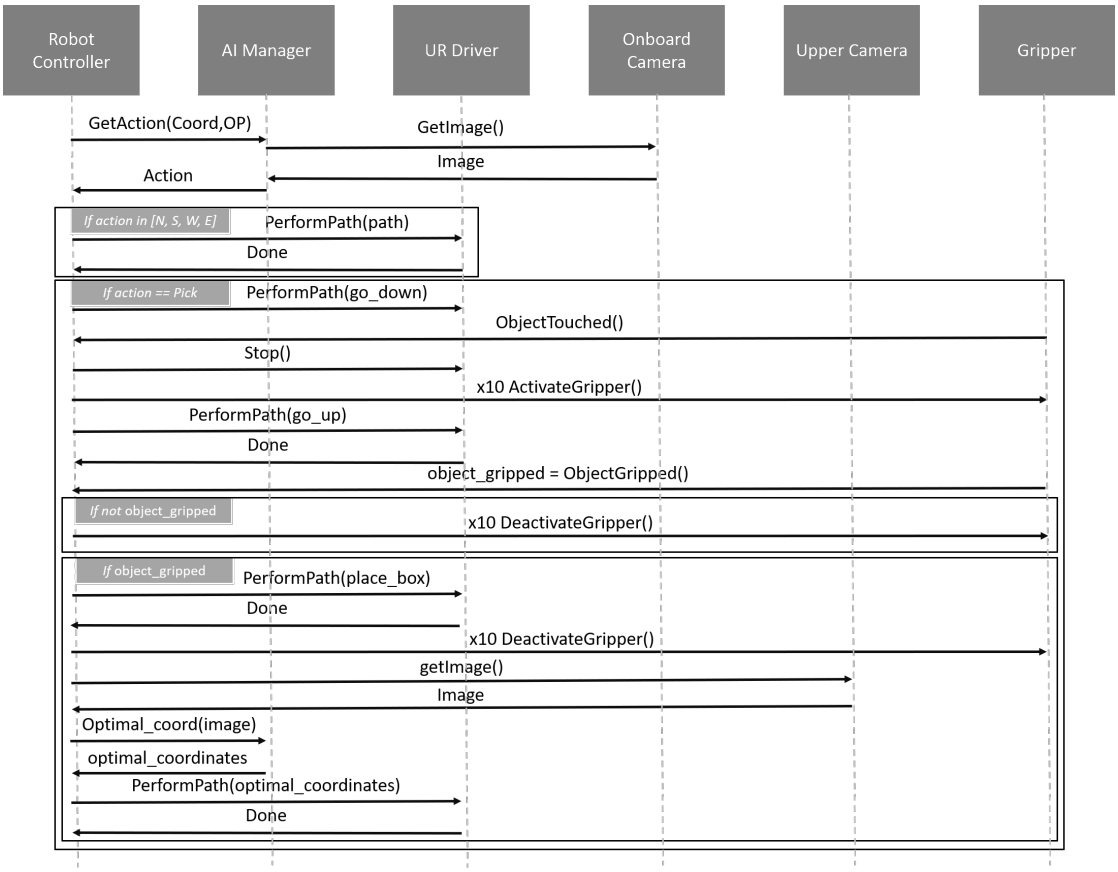


Fig. 5.9: Flow Chart of nodes interacting

To understand better all the architecture, in Figure 5.9 we can find a flow chart showing the iteration between nodes in one step. This flow would be in an infinite loop until the training is over. We can see how the step always starts with Robot Controller Asking AI Manager which action to perform, and AI Manager retrieving a picture from Onboard Camera to decide the action and train the Reinforcement Learning Algorithm. Behind this steps there is a complex process that we will talk about later.

Then, depending on the action to perform, the flow would be really simple or more complex. If action is Pick, the robot has to start an asynchronous downward movement that will only be stopped once Robot Controller receive a True Message in the $\backslash$***distance*** topic, which means that the robot is now in contact with an object. Then, it will activate the gripper, go upwards to the original position and, if the robot has picked an object, perform a place action to put the object in the

place box.

This is a really simplified flow, but its a very good graphical way of understanding how the system works. To go deeply into the system, lets analyse each node separately:

5.3 ai_manager

ai_manager module is the "intelligence" of the robot, responsible for making it learn by training a Deep Reinforcement Learning Algorithm. Using this algorithm, the robot (**agent**) will explore the **Environment** by performing a set of **actions**. Once these actions are performed, the agent will receive a **reward** that can be positive, neutral or negative depending on how far the agent is from the objective.

Each time the agent perform an action, it reaches a new **state**. States can be transitional or terminal, when the agent meets the objective or when it gets to a forbidden position. Each time the agent reaches a terminal state, an **episode** is ended, and a new one is started.

The code of the AI Manager can be found in the appendix of this document, where a link to the github repository can also be found.

5.3.1 Definition of the problem

The objective of the agent is thus the first thing that has to be defined. In this case is simple: pick a piece.

Then, the environment, the states and the actions have to be defined together. These decisions are conditioned by the hardware and materials available. In our case, as said before, we have a UR3 robot with six different points of movements, and a vacuum gripper. That means that the best way of griping an object is by facing the gripper to the floor and move it vertically until it gets in contact with the object, where the vacuum can be powered on, and we can know if the object has been griped or not.

Having this in mind, we have decided that the robot have to be fixed in a specific height with the gripper facing down. Then, the actions will be "north", "south", "east" or "west" to move the robot through the x-y plane formed by these movements in the selected robot height, "pick", to perform the gripping process

described before and place the object in the box, and "random_state" to move the robot to a new random state when a terminal state is reached.

5.3.2 Environment.py

The environment is defined in Environment.py class. There, we can find different parameters and methods. All of them are explained in the code, but we will briefly explain them here. The CARTESIAN_CENTER and the ANGULAR_CENTER represent the same point in the space, but using different coordinates. This point should be the x-y center of the picking box with the robot height defined before as z point. As starting point, we need to use the ANGULAR_CENTER because we want the robot to reach this point with the gripper facing down.

Then, we have to define the edges of the box as terminal states, because we just want the robot to explore inside the box. To define those limits, we use X_LENGTH and Y_LENGTH parameters, which are the X and Y lengths of the box in cm.

Other important parameters to define are the center of the box where we will place all the objects (PLACE_CARTESIAN_CENTER) or the distance that the robot has to move in each action (ACTION_DISTANCE).

Finally, the methods defined in this class are:

- ***generate_random_state(strategy='ncc')***, which is used when the agent reaches a terminal state and needs a new random state.
- ***get_relative_corner(corner)***, which returns the relative coordinates of a corner of the box
- ***is_terminal_state(coordinates, object_gripped)***, which returns a boolean telling whether a given state is terminal or not using the parameters given.

5.3.3 Rewards

Rewards are one of the most difficult-to-define parameters. In this case, rewards are deffined in the EnvManager inner class of RLAlgorithm.py. The specific value of the rewards are not given here because they are different from one training to another, but we give (positive or negative) rewards for:

- Terminal state after picking a piece.
- Terminal state after exceeding the box limits.
- Non terminal state after a pick action
- Other non terminal states

5.3.4 Algorithm

This Deep Q Learning algorithm is implemented in the class RLAlgorithm.py following this schema:

- Initialize replay memory capacity.
- Initialize the policy network with random weights.
- Clone the policy network, and call it the target network.
- For each episode:
  - Initialize the starting state.
  - For each time step:
    - Select an action via exploration or exploitation
    - Execute selected action and observe reward and next state.
    - Store experience in replay memory.
    - Sample random batch from replay memory.
    - Preprocess states from batch.
    - Pass batch of preprocessed states to policy network.
    - NN training. Weight back-propagation:
      - Calculate loss between output Q-values and target Q-values.
      - Using both the target and the policy networks to increase stability.
      - Gradient descent updates weights in the policy network to minimize loss.
- After X time steps or episodes, weights in the target network are updated to the weights in the policy network.

This schema is a little bit difficult to understand in the first moment, but it is deeply explained in the State of The Art section of this document.

RLAlgorithm.py

RLAlgorithm.py is the most important file of this module because it is the place where the algorithm implementation is done. Several classes have been used to implement the algorithm. Some of these classes are defined inside RLAlgorithm (inner classes) and others are normal outer classes. In RLAlgorithm.py, we define the RLAlgorithm class, which also have several inner classes. These classes are:

- **Agent:** Inner class used to define the agent. The most important thing about this class is the select_action method, which is the one used to calculate the action using whether Exploration or Exploitation.
- **DQN:** Inner class used to define the target and policy networks. It defines a neural network that have to be called using the vector of features calculated by passing the image through the feature extractor net.
- **EnvManager:** Inner Class used to manage the RL environment. It is used to perform actions such as calculate rewards or gather the current state of the robot. The most important methods are:
  - **calculate_reward**, which calculates the reward of each action depending on the initial and final state.
  - **calculate_reward**, which calculates the reward of each action depending on the initial and final state.
  - **extract_image_features**, which is used to transform the image to extract image features by passing it through a pre-trained CNN network that can be found in ImageModel Module.
- **EpsilonGreedyStrategy**: Inner Class used to perform the Epsilon greede strategy
- **QValues:** Inner class used to get the predicted q-values from the policy_net for the specific state-action pairs passed in. States and actions are the state-action pairs that were sampled from replay memory.
- **ReplayMemory:** Inner Class used to create a Replay Memory for the RL algorithm
- **Environment:** Class where the RL Environment is defined
- **TrainingStatistics:** Class used to store all the training statistics. If it is run separately, It will plot a set of graphs to represent visually the training evolution.

- **ImageModel:** Class used to extract the image features used in the training. You can find this class in this repository, which store another module of this project.
- **ImageController:** Class used to gather and store the relative state images from a ros topic.

In order to implement the algorithm there are two important structures that are defined in the beginning of this file. These structures are:

- **State**, which defines all the things needed to represent a State:
  - Coordinates of the robot.
  - Image of the State.
  - Boolean telling if an object has been gripped.
- **Experience**, which represents the experience of the agent in a given moment:
  - The initial state of the agent (Image).
  - The initial coordinates of the agent.
  - The action taken by the agent.
  - The state reached after taking the action (Image).
  - The coordinates reached after taking the action.
  - The reward obtained for taking this action.
  - Boolean telling whether the final state is terminal or not.

Finally, there are some important methods in RLAlgorithm class that it is important to take into account to understand how this node works:

- **save_training:** Method used to save the training so that it can be retaken later. It uses pickle library to do so and stores the whole RLAlgorithm object because all the context is needed to retake the training. This method also stores a pickle a TrainingStatistics object for them to be accessible easily.
- **recover_training:** Method used to recover saved trainings. If it doesn't find a file with the name given, it creates a new RLAlgorithm object.

– **train_net:** Method used to train both the train and target Deep Q Networks. We train the network minimizing the loss between the current Q-values of the action-state tuples and the target Q-values. Target Q-values are calculated using the Bellman's equation:

$$q_*(s,a) = E[R_t + \gamma max(q(s',a')]$$

– **next_training_step:** This method implements the Reinforcement Learning algorithm to control the UR3 robot. As the algorithm is prepared to be executed in real life, rewards and final states cannot be received until the action is finished, which is the beginning of next loop. Therefore, during an execution of this function, an action will be calculated and the previous action, its reward and its final state will be stored in the replay memory.

5.3.5 Training Flow

This is a really complex process that it is easier to understand watching it graphically.

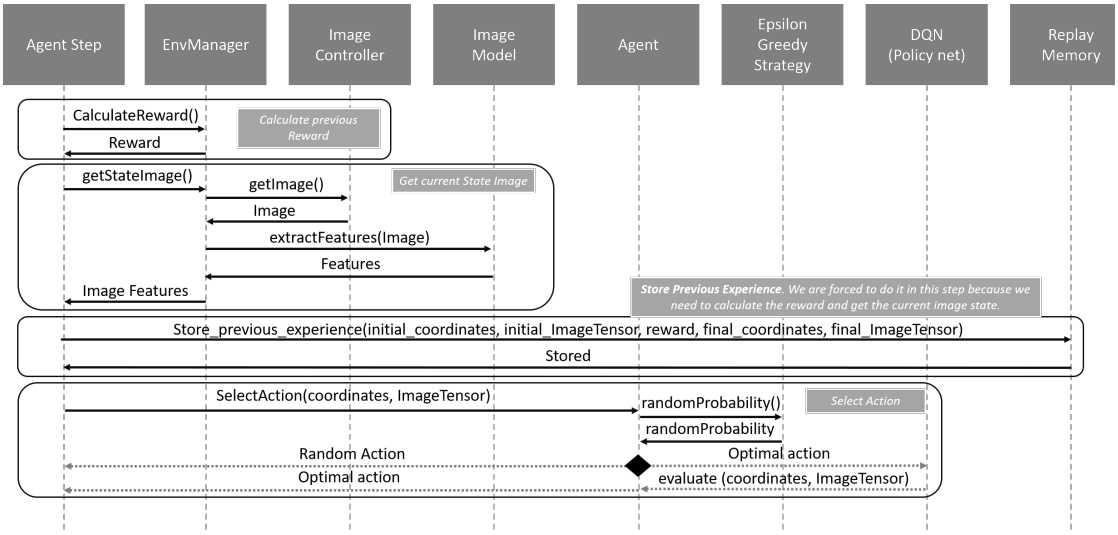


Fig. 5.10: Flow chart explaining training steps

In Figure 5.10, we can see a flow chart explaining what happens during a training step in AI Manager. In the previous section I told that we would explain

deeply what was the training process in AI Manager. We will explain it now with this chart, but, again, it is a simplified flow.

As we can see in the graph, during a training step we have to do basically 2 main tasks. On one hand, we have to calculate the action for the Robot Controller to perform it. The process is simple, we get the current state (Onboard Image and Robot Coordinates), and we pass it through the policy network in order to calculate the Q Value of each action. We get the action with highest Q Value.

On the other hand we have the weird part, which is storing on the Replay Memory the experience of previous step. We have to stor the experience of step t-1 in step t because experience is composed on both initial and final state, and the reward. The initial state is known in step t-1, but the final state is not known until step t-1. The reward of action t-1 is also calculated in step t because it also depends on the final state of the agent.

Finally, we train the algorithm in every step, following the steps shown on Figure 5.11.

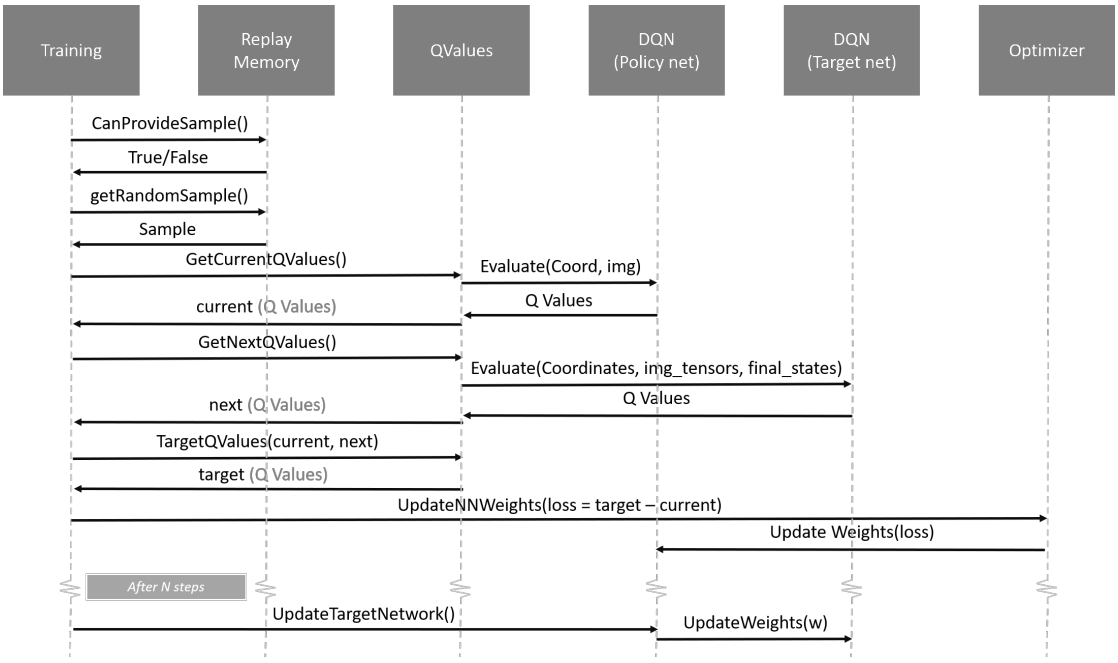


Fig. 5.11: Flow chart explaining the training process

The training precess starts asking the Replay Memory if there are enough ex-

perience to supply a sample of size=batch_size. If there are enough experience, then the Reply Memory provide a random sample of experiences and the training actually starts. The next step would be splitting the batch into batches of categories and calculate the current and next Q Values of all the samples of the batch.

To calculate the current Q Values we use the policy network and to calculate the next Q values we use the target network. To understand why we use different networks it is recommended to read and try to understand the Deep Reinforcement Learning Section of the State of the Art of this document.

The process of calculating the Q Values is also a little bit different in both cases, because for the next Q Value we have to first take out (Q Value = 0) all the samples of the batch in which the final state is terminal.

Once we have the next Q Values calculated, we use the Bellman's Equation to calculate the target Q Values and then calculate the loss as the difference between the target Q Values and the current Q Values.

Finally, we back-propagate the loss using the optimizer, to modify the weights of the policy neural network. The weights of the target neural network are frozen and only updated after X steps.

5.3.6 Image Model

Image model is the module which is connected to AI Manager and is in charge of extracting the features of the images. It uses some Data augmentation techniques to pre process the image, and then it is passed through a Convolutional Neural network to extract its features.

We will talk about this later, but this is a really important step, not only because a good feature extraction is vital for training any neural network, but also because the size reduction of the image allows us to store a huge amount of experiences in the GPU memory without having to discard any of them because of memory problems.

However, we will not analyse this module more deeply because it was not developed by me and for the aim of this document it works just as a Black Box. The author of this module was Pilar Hernandez, that worked together with me in the project.

5.4 Robot Controller

If the AI Manager is the intelligence of the system, if we continue with the human analogy, the Robot Controller would be the body of the system. As we saw in the Figure 5.4, the Robot Controller is the central node, most of the nodes communicates with it, so it is a really important node

Anyway, its complexity is much lower than the AI Manager complexity. The most important task of Robot Controller is to define the set of movements of all the actions. Just to remember, the actions are the ones showed in Figure 5.12, and Robot Controller will use the UR ICAM MoveIt implementation to perform these actions.

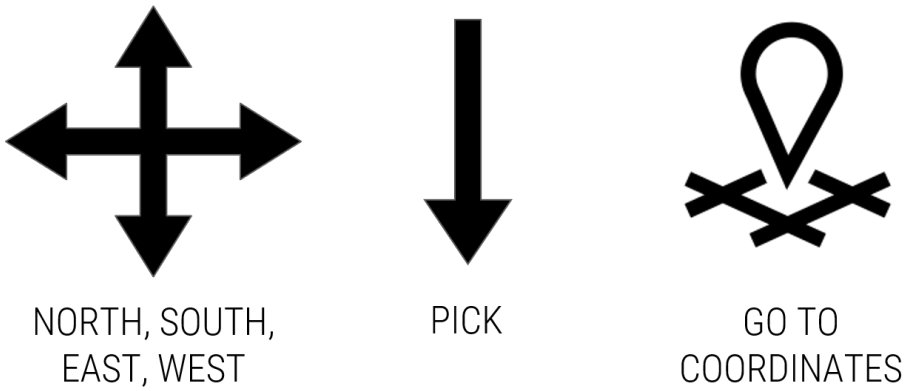


Fig. 5.12: Available actions

With MoveIt, you can tell the robot to go to a specific set of coordinates and it will automatically calculate the best path to reach this position. However, during the implementation of Robot Controller, we found problems executing this kind of movements, because the UR ICAM module wasn't calculating the path correctly, and the robot crashed against itself multiple times.

The solution to this problem was simply stop using this kind of movement, or, at least, to simplify the movement. We realised that we could perform without errors relative movements in every axis, that is to say that we could perform a movement over the axis X, a movement over the axis z but separately, not together. We called this relative move.

Let's see how Robot Controller works. In Robot Controller there are multiple files, but only two important files:

- ***Robot.py***: In this file we use UR ICAM to implement some methods as relative_move(x, y, z), and implement all the actions.
- ***main.py***: In this file we basically implement an infinite loop in which asking the service get_actions for actions and executing them.

5.4.1 Robot.py

Robot.py is a python Class that implements a set of methods. It is important to say that Robot.py is also using the Environment.py class that we created in AI Manager, to retrieve all the information about the Environment. We have done it this way to make it easy to change the parameters of training in both AI Manager and Robot Controller at the same time.

The methods implemented are:

- ***relative_move(self, x, y, z)***: this function takes as parameter the distance in meters to move through each axis. The distance can be positive or negative, and the method will calculate and execute the movements to reach this position.
- ***calculate_relative_movement(self, relative_coordinates***: This method will be used to calculate the relative moves needed to reach certain coordinats. You can see that the parameter passed is called relative_coordinates. This is like that because we are talking about the coordinates of our environment and not the coordinates of our robot. This make the calculation more difficult, because in UR ICAM we can only get the current Cartesian coordinates of the robot, but not the position of the robot into our environment.

  To calculate the relative moves needed, though, we will have to translate the relative coordinates on robot coordinates as *Environment.CARTESIAN_CENTER - relative_coordinates* and then calculate the difference between the result and the robot current cartesian coordinates.
- ***calculate_current_coordinates(self)***: This method is the opposite problem, we use it to translate from robot Cartesian coordinates to Environment coordinates, and we use it to calculate the position of the robot into our environment.
- ***take_north(self, distance=Environment.ACTION_DISTANCE)***: This is the north action of the model. It is basically a relative movement of size Environment.ACTION_DISTANCE in the x axis.

- ***take_south(self, distance=Environment.ACTION_DISTANCE)***: This is the south action of the model. It is basically a negative relative movement of size Environment.ACTION_DISTANCE in the x axis.

- ***take_east(self, distance=Environment.ACTION_DISTANCE)***: This is the east action of the model. It is basically a negative relative movement of size Environment.ACTION_DISTANCE in the y axis.

- ***take_west(self, distance=Environment.ACTION_DISTANCE)***: This is the west action of the model. It is basically a relative movement of size Environment.ACTION_DISTANCE in the y axis.

- ***send_gripper_message(self, msg, timer=2, n_msg=10)***: This is a method used to activate or deactivate the gripper. It sends a burst of messages to ensure that the gripper really switch its state and waits a little bit to allow the robot to pick a piece.

- ***take_pick(self)***: This is the pick action of the model. To perform this action we have to use a new kind of movement: asynchronous relative movement. It is the same movement than before, but we can execute code during the execution of the movement.

  We need to execute code during the movement because we do not know how far the pieces are, so we have to start going down and, during the execution, check the distance topic in order to know when to stop. Once the robot is in contact with an object, the gripper will send a message to the distance topic, Robot Controller will receive it and will stop the movement.

  Finally, we activate the gripper using send_gripper_message(), will go up to the original position, and will check if the robot has picked an object or not. If it hasn't picked an object it will switch the gripper off and would finish the action, but if it has picked an object, it will execute the take_place() action.

  To understand better this action, you can check the flow diagram showed in Figure 5.9.

- ***take_place(self)***: This is the place action. This is not actually an action of the model, because it theoretically belongs to the pick action, but in the implementation of Robot.py we decided to split the method in two different actions.

  In this action, the robot goes to the place position and then switch the gripper off. In this moment, it take a picture of the environment from the Upper Camera node. Using this picture and the Block Detector analysis, it

will calculate the point of the box with a bigger amount of pieces, and will send the coordinates to the take_random_state() action.

– ***take_random_state(self)***: This is the action used to reach some coordinates of the box. Probably the name is not the best, if I had to renamed it now I would called it go_to_initial_state(), but at the beginning of the implementation the idea was to make this movement randomly and it took the name from it.

5.4.2 Block Detector

This module is used by Robot Controller but wasn't developed by me, so I will only introduce the goal of the module and what it does, because for the aim of this project it is like a black box. The author of this module was Pilar Hernandez, that worked together with me in the project.

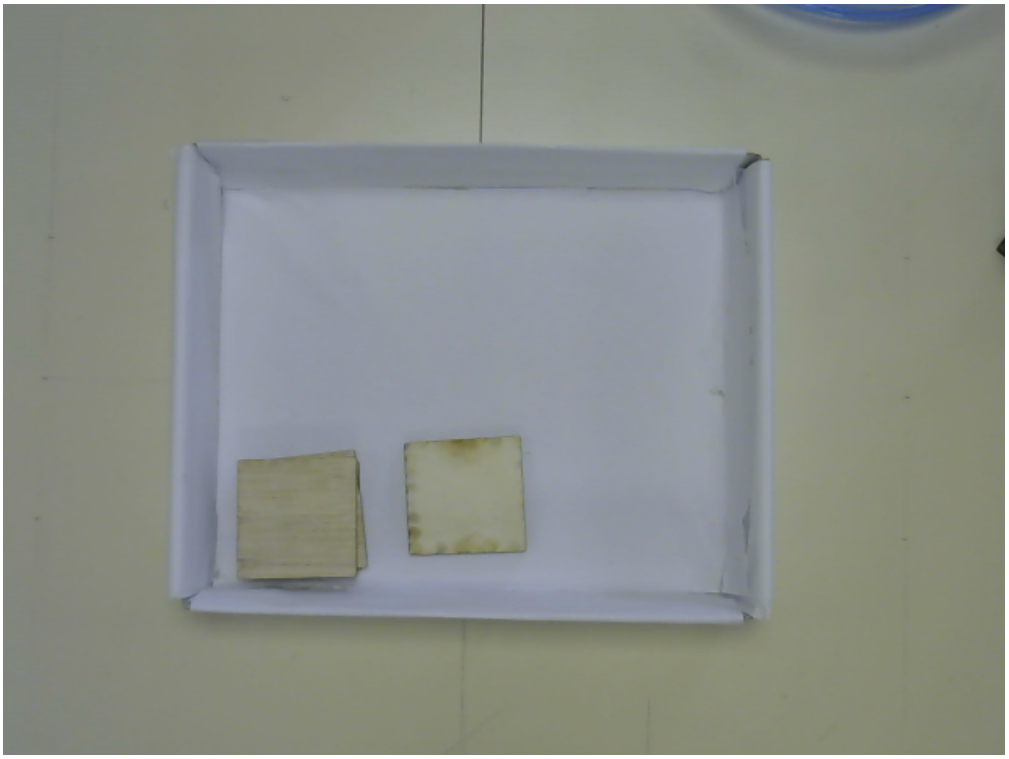


Fig. 5.13: Upper View of the environment

This module is used during the place action in order to know in which point of

the box we should start the next episode. Once the robot had placed the object, it would take a picture from the environment as the one showed in Figure 5.13. Robot Controller would pass the image to the Block detector, which would perform a test similar to the one in Figure 5.14, in which it has calculated all the shapes of the image, and it has calculated the place inside the box with a higher amount of points detected

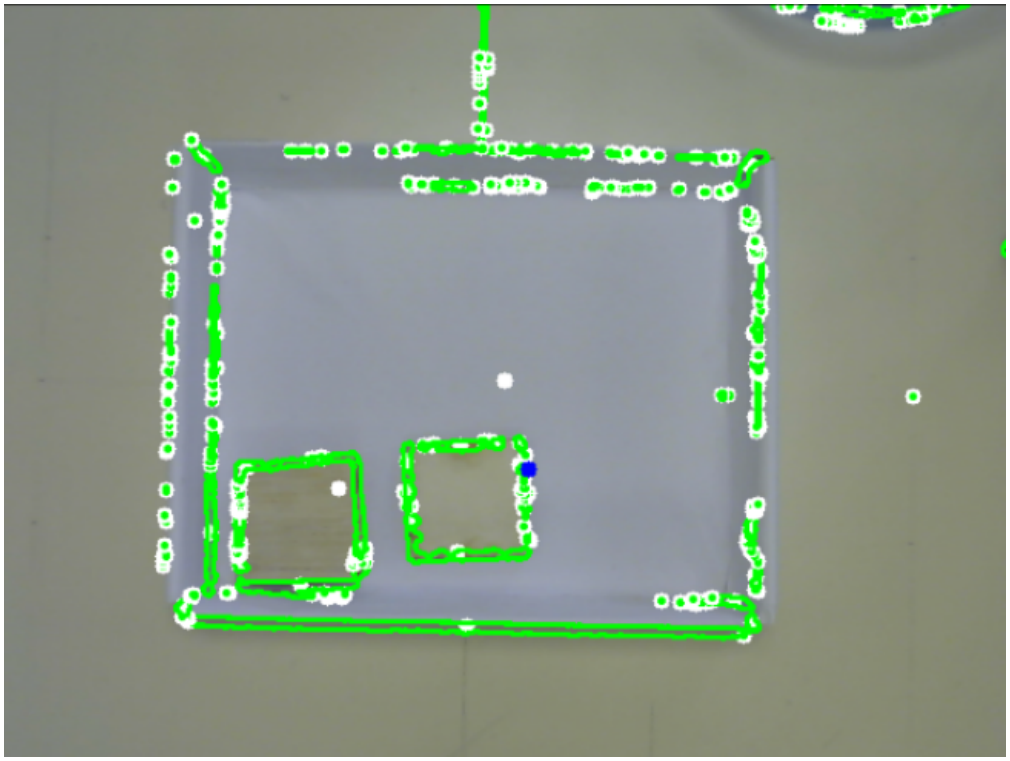


Fig. 5.14: Block Detector working

As we can see in the Figure 5.14, where the blue point would represent the return point of the robot, the block detector haven't probably selected the optimal point, but it is a good one, because it is close to a piece when most of the box is empty.

5.5 Gripper

This node is the last one of our architecture. Just to remember, we decided to use a vacuum gripper because it is really easy to pick object with it. Obviously there

are objects that you cannot pick with it, but when you can, you just have to push your gripper against the object and activate the pump. The gripper used is the one showed in Figure 5.15.

This node is running over an arduino card, which is the controller of the gripper. In the arduino card we have three different peripherals:

Fig. 5.15: Front view of the gripper

- **Contact sensor:** This is the one that detects if the gripper is in contact with an object. It isn't really a contact sensor, as we can see in Figure 5.15, the sucker has actually a mechanical system that can go down or up about 1cm. When a robot touches an object, this object pushes up the sucker and, when the bar goes up it pushes a switch, which is actually the sensor.

  It was really difficult to design and make this system work, but we will talk later about that.

- **Object gripped sensor:** To detect if an object has been gripped or not, we have used an air flow sensor. to make it work we connected it as a ramification of the main air pipe. This way, it will not detect any air flow when there is no object picked (All the air is taken from outside), but when an object is picked, the air flow from the outside will stop, creating a vacuum in the pipes and activating the sensor.

- **Pump switcher:** the pump has to be activated or deactivated programmatically from the arduino card.

As commented before, to read or control these peripherals we have the following topics:

- ***\distance:*** The gripper is publishing continuously if the gripper is being pushed up or not. Robot Controller wants this information to know when to stop during the pick movement. The Robot basically goes down while ***\distance*** are "False" and stops when they are "True".

- ***\switch_on_off:*** The gripper listens to this topic. When it receives a "True" message it switch the gripper on, and when it receives a "False" message it switch the gripper off.

- ***\object_gripped:*** The gripper is publishing continuously if there is an object gripped or not. Robot Controller use this information during the pick action. When this action is finished, robot controller checks if an object has been picked or not by reading from this topic. If an object has been picked it goes to the box to place the object and, if not, it just finishes the pick action and request AI Manager for a new action.

5.6 Algorithm and System optimization

Reaching the final version of the system and the algorithm was a really complex and progressive exercise. It is impossible to narrate here all the decisions that we had to make in the process, but I will try to explain the most importants.

5.6.1 Performance

Deep Reinforcement learning can be a really intense CPU and RAM consumer. In fact, during the firs steps of the training the time betwen two actions were between 3 and 5 seconds. This may not look a lot, but having in mind that a Reinforcement Learning training can have more than 10000 steps, we would loose between 30000 and 50000 seconds just calculating actions (We would have to execute them later). In hours, it would be between 8 and a half hours and 13,8 hours.

We had to solve it, so we tried installing a Nvidia GPU in the computer together with the CUDA drivers. After hours of installation, the results were amazing. We designed a load test to test it and these are the results:

	CPU	GPU
raiv2	3:53 minutes	49 minutes
dl	3:14 minutes	36:31 minutes

Tab. 5.1: Difference in performance between CPU and GPU trainings

In the table we can see the time difference between CPU and GPU and between raiv2 and dl. raiv2 is de development computer and dl the execution one, because have a much better GPU and CPU, as it can be seen in the results. It was important to solve this problem, because if we couldn't, we would have to train the network once in each N steps instead of training it in every step.

Another performance problem of Deep Reinforcement Learning has to be with the Replay Memory. In replay Memory we store all the experiences of the agent in order to take smaller samples of experiences to train the algorithm. The problem comes because all the experiences are stored in the GPU memory and, having in mind that in each experience we are saving 2 images, it was impossible to store more than 2000 experiences.

2000 experiences could be enough for the training, but the highest the Replay Memory size, the better. To solve this problem, we decided to store the features extracted from the images instead of the images themselves. With this solution, we introduce a second limitation which is that we heve to finish the training with the same feature extractor that we started it.

However, this isn't a project because we have this limitation anyway, it wouldn't make sense to use a different feature extractor, because the algorithm has been trained with the first feature extractor.

5.6.2 Training

One of the most difficult things in Deep Learning Algorithms is tuning the algorithm. In this case we had to tune two neural networks and the Reinforcement Learning Algorithm. The CNN was training using the images of previous trainings. We performed several days of training with a silly Neural Network. As Reinforcement Learning training it was totally useless, but we used to store and classify thousands of pick images.

The initial image state of every pick action performed was saved together with the success or failure information of the movement. Whith this images and the labels we trained a Neural Network to classify this images, and we used the first layers of this model as feature extractor for the Reinforcement Learning Algorithm.

Then, we had to tune the Reinforcement Learning Algorithm, but we will talk about this in the analysis and results section of this document.

5.6.3 Why to use Block Detector?

During the first steps of the training, we were doing normal training and, every time that an episode was ended, either by reaching the environment limits or by picking a piece, the robot was starting a new episode by going to a new random pair of coordinates. This looked as the best option at the beginning, because it was the simplest solution, and also because we wanted to ensure low correlation between consecutive steps and random decisions are sometimes the best way of reaching low correlation between samples.

However, during these first episodes we observed that the robot was emptying the pieces of the centre of the box, but it was more difficult for it to pick

the pieces that were near to the edges. The coordinates were chosen completely randomly, so we then realized that, although the coordinates probability distribution of the starting point of the episode was uniform, the probability of passing through the centre of the environment during an episode was actually higher than the probability of reaching the box sides.

The explanation of this is simple, when the initial point of the Episode is in the centre, the probability of reaching any of the four sides of the box is the same while, when the initial point of the environment is one of the sides, its much more complicated to reach another side of the box without passing through the centre.

To check this theory we included the coordinates of ech step in the training statistics, an the results were the ones showed in Figure 5.16. In this image we can see the heatmap of the movements of the robot and how the probability of reaching the centre of the box was mucho more higher than the probability of reaching the sides.

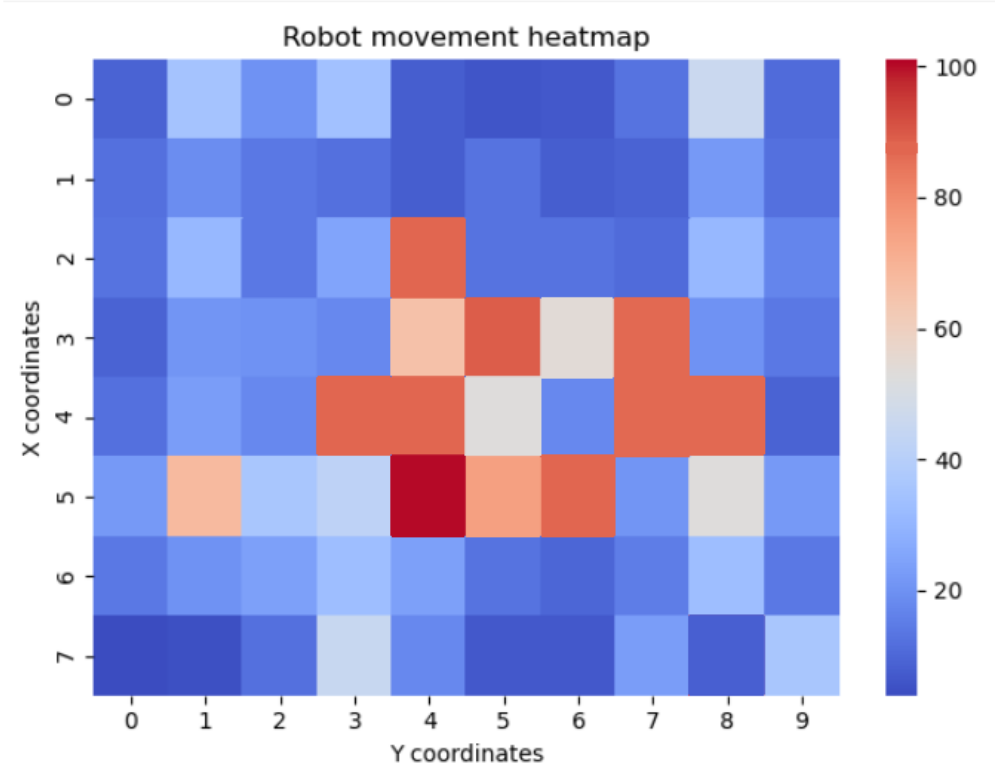


Fig. 5.16: Robot position Heatmap

In an ideal algorithm, this distribution should be uniform, because the distribution of pieces in the box is uniform. To solve this problem, we used a new strategy for calculating the initial point of the environments. In this case, we decided not to send the robot to de centre of the box, that is to say, sending it always to the sides. With this strategy, we knew that the robot was going to pass through the centre of the box, but we was not expecting the distribution of probabilities to be as uniform as it was. The results were really good, as can be seen in the Figure 5.17

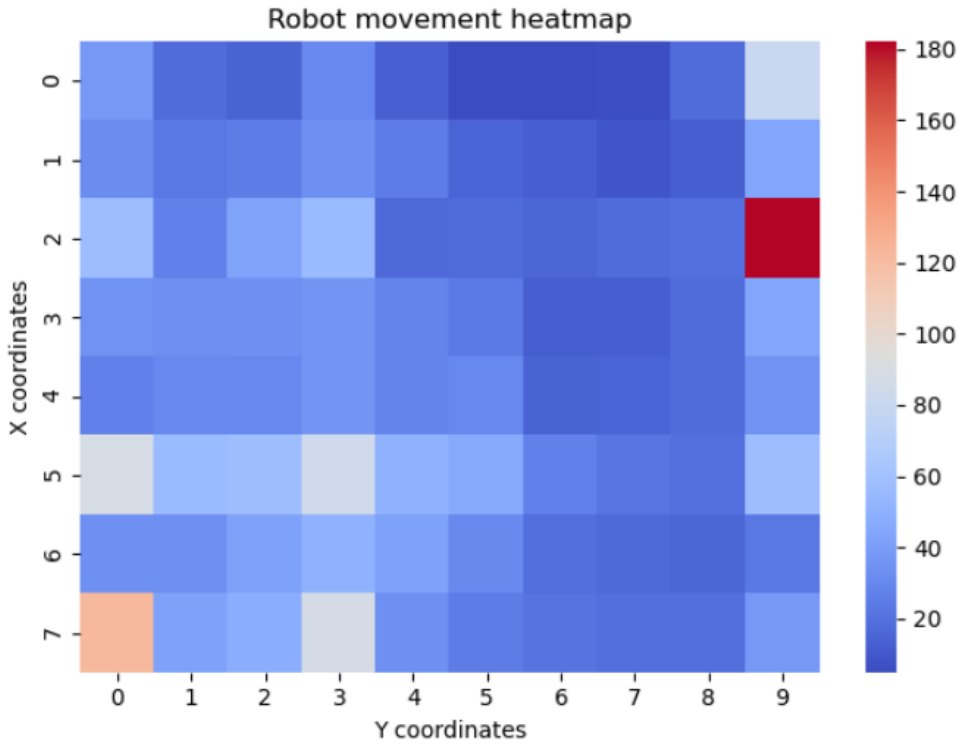
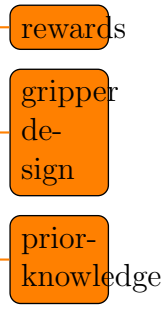


Fig. 5.17: Robot position Heatmap with the new strategy

The robot behaved better with this new strategy, because now it was managing to empty better the sides of the box. However, there was another problem that we had with both strategies. The problem was that, when the box was almost empty, as the initial position of each episode was chosen randomly, most of the times the robot was going to places with no pieces, and it was taking a lot of time to empty the full box. The robot was working correctly with the box full of pieces, but not were there were just few of them.

To solve this problem, we decided to implement the Block Detector. We commented it before, so I will not explain again how it works, but the important thing is that it allowed us to move the robot to the places with highest amount of pieces, making the robot performance great with or without a high amount of pieces. The best thing is that, as the place with highest amount of pieces varies during the training, the distribution of the robot position kept constantly distributed during the whole box.



6. RESULTS ANALYSIS

In Reinforcement Learning, results vary a lot depending on the parameters of the training. To understand how we are going to compare the different algorithms, we have to first define some metrics. In this case, the metrics are:

- **The number of pick actions per episode**: When the agent performs a pick action and picks an object, the episode is ended. So, in this case, **the lowest the better**.
- **Reward per episode**: In each episode, the agent is trying to maximize the total reward, so, in this case, **the highest the better**
- **Number of steps per episode:** We want to minimize the time between picks. **The lower the better**
- **Evolution of successful episodes during the training:** As we already know, the episodes can be ended because the agent has pick an object (success) or when the robot has reached the environment limits (not success). The number of unsuccessful episodes should decrease during the training.
- **Random actions per episode:** This is not actually a measure of performance but a measure of control. If the training is going well, when the number of random actions decreases, the rest of the measures should improve.

Once that we have the measures, we should understand how to compare this information. For example I have decided that, for the first 3 measures, we shouldn't take into account the information of unsuccessful episodes, because that could result on a false sense of improvement. Let's imagine the "Number of steps per episode" metric, if we took into account the non successful episodes, we could have an episodes of one steps thinking that we are improving, while we are actually worsen. The same could happen with the number of picks and even with the reward metric, because, although the reward for reaching the environment limits

is really low, the reward of a failed pick is as low as the other, so we could also be having a false sense of improving.

On the other hand, in order to have softer and more readable graphs, I have decided to plot the mean of the last N values instead of the values themselves. I probably got inspiration from the "Theory of Communications" course.

The results gotten can be seen in the following set of figures. In Figure 6.1 we can see how the pick actions per episode decreased during the training. The mean was between 1.2 and 1.4 which are goods results having in mind that we are only showing the successful episodes. The optimal value of this metric would be 1 pick per successful episode, so this results shows that there are much more successful picks than unsuccessful.

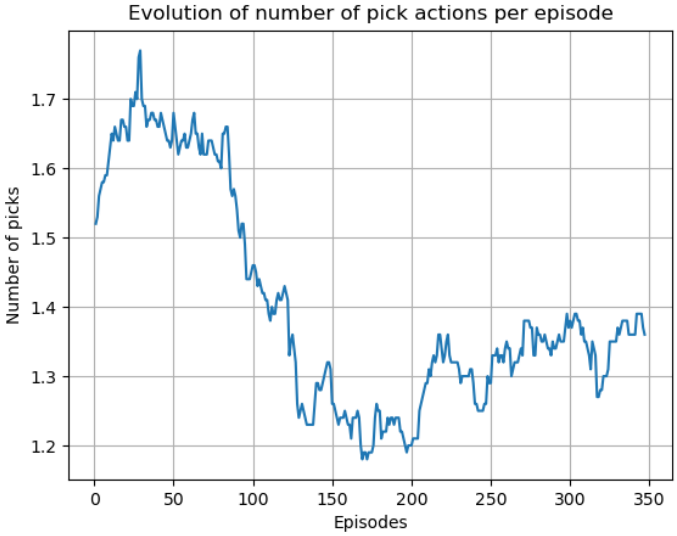


Fig. 6.1: Evolution of pick actions in episodes

In Figure 6.2, we can see how rewards evolve during the training. As we can see, the reward is increasing during the whole training. The reward is still negative but it is normal, because all the actions have negative rewards but the successful pick action, that has a positive reward.The objective of the training would be having positive rewards, that would mean picking a piece in the first 10 steps of the episode without failing any other pick. This is a performance that, unfortunately is still far from happening, although our performance is good enough to reach our objectives, as we will see later.

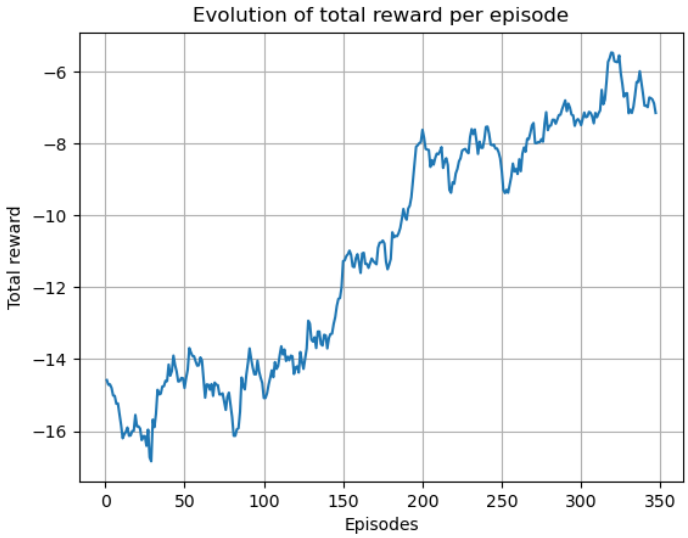


Fig. 6.2: Evolution of rewards through episodes

In Figure 6.3, we can see the evolution of steps per episode. This metric has improve a lot, as we can see that the agent is picking pieces much faster than in the beginning.

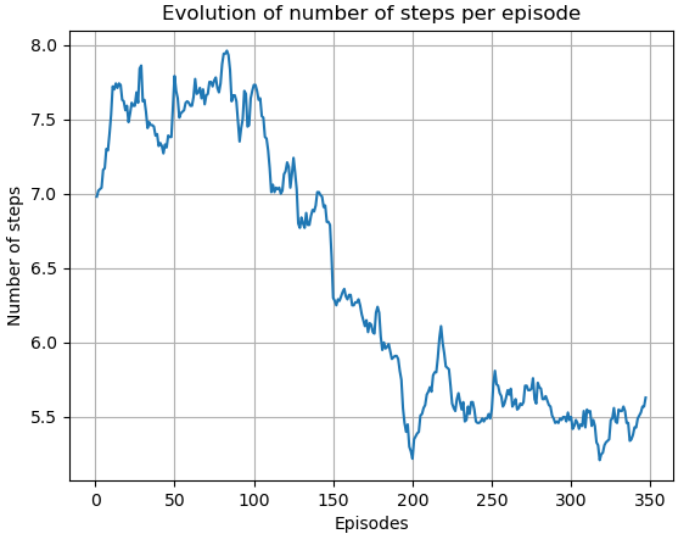


Fig. 6.3: Evolution of steps through episodes

As we said before, the improvement in the other metrics is important, but we have to check if this is happening when we reduce the number of random actions. If it doesn't, it can just be coincidence. In Figure 6.4 we can see how the random actions kept decreasing during the training, showing that the good impressions of the training are well founded.

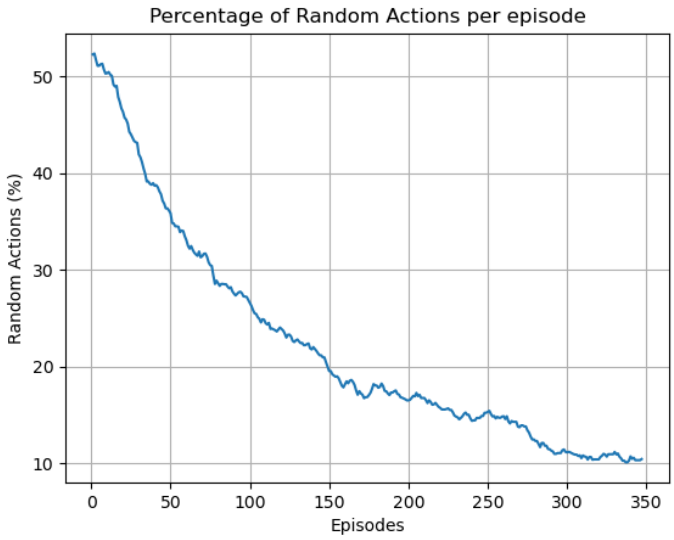


Fig. 6.4: Evolution of random actions per episode

Until now, all the news regarding were good. However, we cannot be completely happy with the results showed in Figure 6.5. In this image we can see how successful and non successful episodes have evolved during training. Having in mind that the big white holes (set of unsuccessful episodes) can be considered as accidents during the training (forgetting to re-fill the box with pieces, or failures of the system while calculating the robot coordinates), it seems like the rate of successful vs unsuccessful episodes improve over the training.

However, This is probably the worst metric in the training, and it is something to improve in the next iterations. If I had to say the reason, I would say that sometimes, when the box is partially empty, the agent sees reaching the environment limits as a tool for picking a piece, because every time that the robot reaches the limits, the optimal point of starting is calculated.

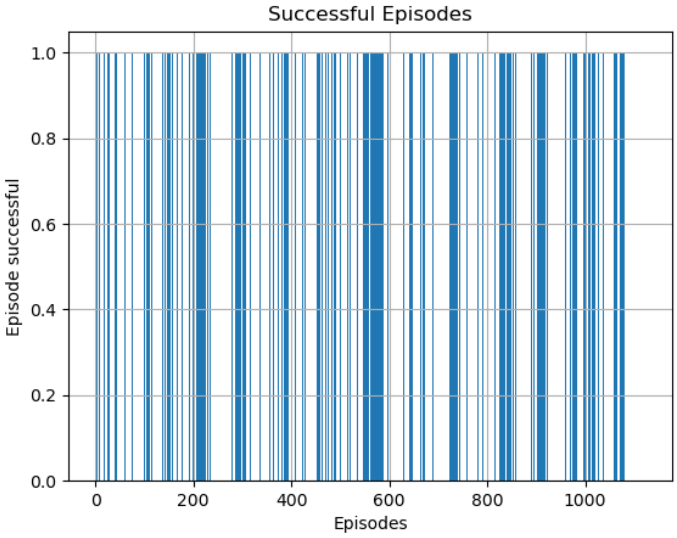


Fig. 6.5: Evolution of successful episodes during training

7. CONCLUSIONS AND FUTURE WORK

In the previous section we talked about the results, but the most important thing that we have to do when analysing the results of a project is compare the results with the objectives. Just to remember, the objectives of the project were the following:

- Implement a bin picking simple solution. A basic one, without Artificial Intelligence.
- Improve the performance using RL and Image Recognition.
- Study the usage of new technologies to add information to the system.
- Create a functional system that can be continued and that delivers the first results.
- The system should empty the box with a rhythm of 2 pieces per minute.

It is important to have in mind that the project is not a fully functional system. We couldn't probably sell the product to anyone in this state, but taking into account the complexity of the project, that we were starting from zero and th results obtained, I would say that we have reached the expectations.

Analysing the objectives, we have implemented a simple and complex bin picking solution, studying and adding new technologies such as the Block Detector or Prior Knowledge. Besides, we have implemented a functional system that has to be improved, but it works in a good way, improving the objective of picking 2 pieces per minute in almost 20 seconds.

This last objective may not seem a lot, but it is important to take into account that the system has been implemented in a real robot, and just the pick and place action can take about 30 seconds to be taken.

During the whole project we have passed through a lot of adversities. It was difficult to make the communication between ROS nodes work, the development of the home made gripper took more time than expected, there were a national lock down in France that last over 2 months... In every moment we knew that we were on a project and that all these things could happen. If we were locked i some task, we managed to find a complementary task in order to not being stopped.

In my opinion, we have done a really good job and we have proven that Reinforcement Learning is a good solution for this kind of problems. The solution implemented is still far from its final version, but we have created a really good starting point for other people. I am glad that the project will be followed in the following months and it will probably reach a much better state.

The solution implemented was working, but I think that there is still a lot of work to do. For example, the agent was learning that when the background of the images was white (No pieces in the box), he shouldn't perform a pick action. We tested for a long time, and if there were no pieces in the box, the robot was rarely performing pick actions, coinciding with the minimum random action ratio.

However, in my opinion, the agent wasn't really detecting the best place for taking a pick action, but the worst, and it was performing pick actions in the rest of the places. There is a lot of work to do on fine tuning the Algorithm to find its optimal state. Probably with hours and hours of training it will be possible.

There are other important things to do in the project, as trying to generalize the model in order to be able to pick not only the wooden squares but any other kind of objects. In order to do so, it will take a lot of hours of training with some different objects.

APPENDIX

.1 Robot Controller

En esta sección se muestra el código de algunos de los principales elementos del módulo Robot Controller, implementado en la arquitectura del proyecto.

Este código también está disponible en el siguiente repositorio de github:

https://github.com/pabloiglesia/robot_controller

.1.1 main.py

```
#!/usr/bin/env python
# coding: utf-8

"""
- We need to connect the camera and the nodes
roslaunch ur_icam_description webcam.launch

- We need to establish a connection to the robot with the
    following comand:
roslaunch ur_robot_driver ur3_bringup.launch robot_ip
    :=10.31.56.102 kinematics_config:=${HOME}/Calibration/
    ur3_calibration.yaml

- Then, we ned to activate moovit server:
roslaunch ur3_moveit_config ur3_moveit_planning_execution.launch

- Activate the talker
rosrun ai_manager main.py

- Activate the node
rosrun robot_controller arduino.py

- Finally, we can run the program
rosrun robot_controller main.py

"""

import rospy

from ai_manager.srv import GetActions
from Robot import Robot


def get_action(robot, object_gripped):
```

```
32      relative_coordinates = robot.calculate_current_coordinates()
33      rospy.wait_for_service('get_actions')
34      try:
35          get_actions = rospy.ServiceProxy('get_actions', GetActions
        )
36          return get_actions(relative_coordinates[0],
        relative_coordinates[1], object_gripped).action
37      except rospy.ServiceException as e:
38          print("Service call failed: %s"%e)
39
40
41  # This function defines the movements that robot should make
        depending on the action listened
42  def take_action(action, robot):
43      rospy.loginfo("Action received: {}".format(action))
44      object_gripped = False
45      if action == 'north':
46          robot.take_north()
47      elif action == 'south':
48          robot.take_south()
49      elif action == 'east':
50          robot.take_east()
51      elif action == 'west':
52          robot.take_west()
53      elif action == 'pick':
54          object_gripped = robot.take_pick()
55      elif action == 'random_state':
56          robot.take_random_state()
57      return object_gripped
58
59
60  if __name__ == '__main__':
61
62      rospy.init_node('robotUR')
63
64      robot = Robot()
65
66      # Test of positioning with angular coordinates
67      robot.go_to_initial_pose()
68
69      # Let's put the robot in a random position to start, creation
        of new state
70      object_gripped = take_action('random_state', robot)
71
72      while True:
73          action = get_action(robot, object_gripped)
74          object_gripped = take_action(action, robot)
```

.1.2 Robot.py

```
import copy
import rospy
import time

from std_msgs.msg import Bool
from std_msgs.msg import Float32

from ai_manager.Environment import Environment
from ur_icam_description.robotUR import RobotUR

"""
Class used to establish connection with the robot and perform different actions such as move in all cardinal directions
or pick and place an object.
"""


class Robot:
    def __init__(self, robot=RobotUR(), gripper_topic='switch_on_off'):
        self.robot = robot  # Robot we want to control
        self.gripper_topic = gripper_topic  # Gripper topic
        self.gripper_publisher = rospy.Publisher(self.gripper_topic, Bool)  # Publisher for the gripper topic

    def relative_move(self, x, y, z):
        """
        Perform a relative move in all x, y or z coordinates.

        :param x:
        :param y:
        :param z:
        :return:
        """
        waypoints = []
        wpose = self.robot.get_current_pose().pose
        if x:
            wpose.position.x -= x  # First move up (x)
            waypoints.append(copy.deepcopy(wpose))
        if y:
            wpose.position.y -= y  # Second move forward/backwards in (y)
            waypoints.append(copy.deepcopy(wpose))
        if z:
            wpose.position.z += z  # Third move sideways (z)
            waypoints.append(copy.deepcopy(wpose))

```

```
44          self.robot.exec_cartesian_path(waypoints)
45
46      def calculate_relative_movement(self, relative_coordinates):
47          absolute_coordinates_x = Environment.CARTESIAN_CENTER[0] -
        relative_coordinates[0]
48          absolute_coordinates_y = Environment.CARTESIAN_CENTER[1] -
        relative_coordinates[1]
49
50          current_pose = self.robot.get_current_pose()
51
52          x_movement = current_pose.pose.position.x -
    absolute_coordinates_x
53          y_movement = current_pose.pose.position.y -
    absolute_coordinates_y
54
55          return x_movement, y_movement
56
57      def calculate_current_coordinates(self):
58          absolut_coordinate_x = self.robot.get_current_pose().pose.
    position.x
59          absolut_coordinate_y = self.robot.get_current_pose().pose.
    position.y
60
61          relative_coordinate_x = Environment.CARTESIAN_CENTER[0] -
    absolut_coordinate_x
62          relative_coordinate_y = Environment.CARTESIAN_CENTER[1] -
    absolut_coordinate_y
63
64          return [relative_coordinate_x, relative_coordinate_y]
65
66      # Action north: positive x
67      def take_north(self, distance=Environment.ACTION_DISTANCE):
68          self.relative_move(distance, 0, 0)
69
70      # Action south: negative x
71      def take_south(self, distance=Environment.ACTION_DISTANCE):
72          self.relative_move(-distance, 0, 0)
73
74      # Action east: negative y
75      def take_east(self, distance=Environment.ACTION_DISTANCE):
76          self.relative_move(0, -distance, 0)
77
78      # Action west: positive y
79      def take_west(self, distance=Environment.ACTION_DISTANCE):
80          self.relative_move(0, distance, 0)
81
82      def take_random_state(self):
83          # Move robot to random positions using relative moves. Get
        coordinates
```

```
84          relative_coordinates = Environment.generate_random_state()
85          # Calculate the new coordinates
86          x_movement, y_movement = self.calculate_relative_movement(
    relative_coordinates)
87          # Move the robot to the random state
88          self.relative_move(x_movement, y_movement, 0)
89
90      def send_gripper_message(self, msg, timer=2, n_msg=10):
91          """
92          Function that sends a burst of n messages of the
    gripper_topic during an indicated time
93          :param msg: True or False
94          :param time: time in seconds
95          :param n_msg: number of messages
96          :return:
97          """
98          time_step = (timer/2)/n_msg
99          i=0
100         while(i <= n_msg):
101             self.gripper_publisher.publish(msg)
102             time.sleep(time_step)
103             i += 1
104
105         time.sleep(timer/2)
106
107     # Action pick: Pick and place
108     def take_pick(self):
109         # In this function we should read the distance to the
    object
110         # up_distance = 0  # Variable were we store the distance
    that we have move the robot so that we can go back to the
111         # original pose
112
113         def change_plan_speed(plan, new_speed):
114             """
115             Function used for changing Robot velocity of a
    cartesian path once the movement have been planned.
116             :param plan: RobotTrajectory object. For example, the
    one calculated by compute_cartesian_path() MoveGroup function.
117             :param new_speed: speed factor of the robot, been 1
    the original speed and 0 the minimum.
118             :return: RobotTrajectory object (new plan).
119             """
120             new_plan = plan
121             n_joints = len(plan.joint_trajectory.joint_names)
122             n_points = len(plan.joint_trajectory.points)
123
124             points = []
125             for i in range(n_points):
```

```
126                 plan.joint_trajectory.points[i].time_from_start =
    plan.joint_trajectory.points[
127
        i].time_from_start / new_speed
128                 velocities = []
129                 accelerations = []
130                 positions = []
131                 for j in range(n_joints):
132                     velocities.append(plan.joint_trajectory.points
    [i].velocities[j] * new_speed)
133                     accelerations.append(plan.joint_trajectory.
    points[i].accelerations[j] * new_speed)
134                     positions.append(plan.joint_trajectory.points[
    i].positions[j])
135
136                 point = plan.joint_trajectory.points[i]
137                 point.velocities = velocities
138                 point.accelerations = accelerations
139                 point.positions = positions
140
141                 points.append(point)
142
143             new_plan.joint_trajectory.points = points
144
145             return new_plan
146
147         def back_to_original_pose(robot):
148             """
149             Function used to go back to the original height once a
     vertical movement has been performed.
150             :param robot: robot_controller.Robot.py object
151             :return:
152             """
153             distance = Environment.CARTESIAN_CENTER[2] - robot.
    robot.get_current_pose().pose.position.z
154             robot.relative_move(0, 0, distance)
155
156         def down_movement(robot, movement_speed):
157             """
158             This function performs the down movement of the pick
    action.
159
160             It creates an asynchronous move group trajectory
    planning. This way the function is able to receive distance
161             messages while the robot is moving and stop it once
    the robot is in contact with an object.
162
163             Finally, when there is any problems with the
    communications the movement is stopped and
```

```
164             communication_problem boolean flag is set to True. It
    is considered that there is a problem with
165             communications when the robot is not receiving any
    distance messages during 200 milli-seconds (timeout=0.2)
166 
167             :param robot: robot_controller.Robot.py object
168             :return: communication_problem flag
169             """
170 
171             distance_ok = rospy.wait_for_message('distance', Bool)
    .data  # We retrieve sensor distance
172             communication_problem = False
173 
174             if not distance_ok:  # If the robot is already in
    contact with an object, no movement is performed
175                 waypoints = []
176                 wpose = robot.robot.get_current_pose().pose
177                 wpose.position.z -= (wpose.position.z)  # Third
    move sideways (z)
178                 waypoints.append(copy.deepcopy(wpose))
179 
180                 (plan, fraction) = robot.robot.move_group.
    compute_cartesian_path(
181                     waypoints,  # waypoints to follow
182                     0.01,  # eef_step
183                     0.0)  # jump_threshold
184 
185                 plan = change_plan_speed(plan, movement_speed)
186                 robot.robot.move_group.execute(plan, wait=False)
187 
188                 while not distance_ok:
189                     try:
190                         distance_ok = rospy.wait_for_message('
    distance', Bool, 0.2).data  # We retrieve sensor distance
191                     except:
192                         communication_problem = True
193                         rospy.loginfo("Error in communications,
    trying again")
194                         break
195 
196                 # Both stop and 10 mm up movement to stop the
    robot
197                 robot.robot.move_group.stop()
198                 robot.relative_move(0, 0, 0.001)
199 
200             return communication_problem
201 
202         communication_problem = True
203         while communication_problem:  # Infinite loop until the
```

```
    movement is completed
204             communication_problem = down_movement(self,
    movement_speed=0.2)
205
206         self.send_gripper_message(True, timer=4)  # We turn on the
     gripper
207
208         back_to_original_pose(self)  # Back to the original pose
209
210         object_gripped = rospy.wait_for_message('object_gripped',
    Bool).data
211         if object_gripped:  # If we have gripped an object we
    place it into the desired point
212             self.take_place()
213         else:
214             self.send_gripper_message(False)  # We turn off the
    gripper
215
216         return object_gripped
217
218     # Function to define the place for placing the grasped objects
219     def take_place(self):
220         # First, we get the cartesian coordinates of one of the
    corner
221         x_box, y_box = Environment.get_relative_corner('se')
222         x_move, y_move = self.calculate_relative_movement([x_box,
    y_box])
223         # We move the robot to the corner of the box
224         self.relative_move(x_move, y_move, 0)
225         # We calculate the trajectory for our robot to reach the
    box
226         trajectory_x = self.robot.get_current_pose().pose.position
    .x - Environment.PLACE_CARTESIAN_CENTER[0]
227         trajectory_y = self.robot.get_current_pose().pose.position
    .y - Environment.PLACE_CARTESIAN_CENTER[1]
228         trajectory_z = - Environment.CARTESIAN_CENTER[2] +
    Environment.PLACE_CARTESIAN_CENTER[2]
229         # We move the robot to the coordinates desired to place
    the object
230         self.relative_move(0, 0, trajectory_z)
231         self.relative_move(0, trajectory_y, 0)
232         self.relative_move(trajectory_x, 0, 0)
233         # Then, we left the object
234         self.relative_move(0, 0, -0.05)
235         # Then, we switch off the vacuum gripper so the object can
     be placed
236         self.send_gripper_message(False)
237         # Wait some seconds, in order to the msg to arrive to the
    gripper
```

```
238         time.sleep(2)
239         # Then the robot goes up
240         self.relative_move(0, 0, 0.05)
241         # Final we put the robot in the center of the box, the
    episode should finish now
242         self.robot.go_to_joint_state(Environment.ANGULAR_CENTER)
243 
244     def go_to_initial_pose(self):
245         target_reached = self.robot.go_to_joint_state(Environment.
    ANGULAR_CENTER)
246 
247         if target_reached:
248             print("Target reachead")
249         else:
250             print("Target not reached")
```

.2 Artificial Intelligence Manager

En esta sección se muestra el código de algunos de los principales elementos del módulo AI Manager, implementado en la arquitectura del proyecto.

Este código también está disponible en el siguiente repositorio de github:

https://github.com/pabloiglesia/ai_manager

.2.1 main.py

```
1 #!/usr/bin/env python
2 """
3 Code used to train the UR3 robot to perform a pick and place task
    using Reinforcement Learning and Image Recognition.
4 This code does not perform actions directly into the robot, it
    just posts actions in a ROS topic and
5 gathers state information from another ROS topic.
6 """
7 
8 import rospy
9 import torch
10 
11 from ai_manager.srv import GetActions, GetActionsResponse
12 from RLAlgorithm import RLAlgorithm
13 from Environment import Environment
14 
15 rospy.init_node('ai_manager', anonymous=True)  # ROS node
    initialization
```

```
16 # Global Image Controller
17 RL_ALGORITHM = RLAlgorithm.recover_training(batch_size=256, lr
       =0.0001,
18                                                 others='
       optimal_original_rewards_algorithm1901',
       include_pick_prediction=False)
19                                                 # others = '
       optimal_original_rewards_new_model')
20
21 def handle_get_actions(req):
22     """
23     Callback for each Request from the Robot
24     :param req: Robot requests has 3 elements: object_gripped, x
       and y elements
25     :return:
26     """
27     object_gripped = req.object_gripped
28     current_coordinates = [req.x, req.y]
29     # Next action is calculated from the current state
30     action = RL_ALGORITHM.next_training_step(current_coordinates,
       object_gripped)
31
32     # RL_ALGORITHM.plot()
33
34     return GetActionsResponse(action)
35
36
37 def get_actions_server():
38     """
39     Service initialization to receive requests of actions from the
       robot.
40     Each time that a request is received, handle_get_actions
       function will be called
41     :return:
42     """
43     s = rospy.Service('get_actions', GetActions,
       handle_get_actions)
44     rospy.loginfo("Ready to send actions.")
45     rospy.spin()
46     rospy.on_shutdown(save_training)
47
48
49 def save_training():
50     RL_ALGORITHM.save_training()
51
52
53 if __name__ == '__main__':
54     try:
55         get_actions_server()
```

```
56      except rospy.ROSInterruptException:
57          pass
```

.2.2 RLAlgorithm.py

```
1  # coding=utf-8
2  import math
3  import random
4  import os
5  import errno
6  import sys
7  from collections import namedtuple
8
9  import matplotlib
10 import matplotlib.pyplot as plt
11 import rospy
12 import torch
13 import torch.nn as nn
14 import torch.nn.functional as F
15 import torch.optim as optim
16 import torchvision.transforms as T
17 from PIL import Image
18
19 from Environment import Environment
20 from TrainingStatistics import TrainingStatistics
21 from ImageProcessing.ImageModel import ImageModel
22 from ImageController import ImageController
23
24 is_ipython = 'inline' in matplotlib.get_backend()
25 if is_ipython: from IPython import display
26
27 import pickle
28
29 State = namedtuple(  # State information namedtuple
30     'State',
31     ('coordinate_x', 'coordinate_y', 'pick_probability', '
    object_gripped', 'image_raw')
32 )
33
34 Experience = namedtuple(  # Replay Memory Experience namedtuple
35     'Experience',
36     ('state', 'coordinates', 'pick_probability', 'action', '
    next_state', 'next_coordinates', 'next_pick_probability',
37      'reward', 'is_final_state')
38 )
39
40
41 class RLAlgorithm:
```

```
42      """
43      Class used to perform actions related to the RL Algorithm training. It can be initialized with custom parameters or
44      with the default ones.
45
46      To perform a Deep Reinforcement Learning training, the following steps have to be followed:
47
48          1. Initialize replay memory capacity.
49          2. Initialize the policy network with random weights.
50          3. Clone the policy network, and call it the target network.
51          4. For each episode:
52              1. Initialize the starting state.
53               2. For each time step:
54                  1. Select an action.
55                      - Via exploration or exploitation
56                  2. Execute selected action in an emulator or in Real-life.
57                  3. Observe reward and next state.
58                  4. Store experience in replay memory.
59                  5. Sample random batch from replay memory.
60                  6. Preprocess states from batch.
61                  7. Pass batch of preprocessed states to policy network.
62                  8. Calculate loss between output Q-values and target Q-values.
63                      - Requires a pass to the target network for the next state
64                  9. Gradient descent updates weights in the policy network to minimize loss.
65                      - After time steps, weights in the target network are updated to the weights in the policy network.
66
67      """
68
69      def __init__(self, object_gripped_reward=10, object_not_picked_reward=-10, out_of_limits_reward=-10,
70                   horizontal_movement_reward=-1, batch_size=32, gamma=0.999, eps_start=1, eps_end=0.01, eps_decay=0.0005,
71                   target_update=10, memory_size=100000, lr=0.001, num_episodes=1000, include_pick_prediction=False,
72                   save_training_others='optimal'):
73          """
74
75          :param object_gripped_reward: Object gripped reward
76          :param object_not_picked_reward: Object not picked reward
77          :param out_of_limits_reward: Out of limits reward
78          :param horizontal_movement_reward: Horizontal movement
```

```
    reward
79          :param batch_size: Size of the batch used to train the
    network in every step
80          :param gamma: discount factor used in the Bellman equation
81          :param eps_start: Greedy strategy epsilon start (
    Probability of random choice)
82          :param eps_end: Greedy strategy minimum epsilon (
    Probability of random choice)
83          :param eps_decay: Greedy strategy epsilon decay (
    Probability decay of random choice)
84          :param target_update: How frequently, in terms of episodes
    , target network will update the weights with the
85          policy network weights
86          :param memory_size: Capacity of the replay memory
87          :param lr: Learning rate of the Deep Learning algorithm
88          :param num_episodes:  Number of episodes on training
89          :param include_pick_prediction: Use the image model pick
    prediction as input of the DQN
90          :param self_training_others: Parameter used to modify the
    filename of the training while saving
91          """
92
93          self.batch_size = batch_size
94          self.gamma = gamma
95          self.eps_start = eps_start
96          self.eps_end = eps_end
97          self.eps_decay = eps_decay
98          self.target_update = target_update
99          self.memory_size = memory_size
100         self.lr = lr
101         self.num_episodes = num_episodes
102         self.include_pick_prediction = include_pick_prediction
103         self.save_training_others = save_training_others
104
105         self.current_state = None  # Robot current state
106         self.previous_state = None  # Robot previous state
107         self.current_action = None  # Robot current action
108         self.current_action_idx = None  # Robot current action
    Index
109         self.episode_done = False  # True if the episode has just
    ended
110
111         # This tells PyTorch to use a GPU if its available,
    otherwise use the CPU
112         self.device = torch.device("cuda" if torch.cuda.
    is_available() else "cpu")  # Torch devide
113         self.em = self.EnvManager(self, object_gripped_reward,
    object_not_picked_reward, out_of_limits_reward,
114                                   horizontal_movement_reward)  #
```

```
    Robot Environment Manager
115         self.strategy = self.EpsilonGreedyStrategy(self.eps_start,
     self.eps_end, self.eps_decay)  # Greede Strategy
116         self.agent = self.Agent(self)  # RL Agent
117         self.memory = self.ReplayMemory(self.memory_size)  #
    Replay Memory
118         self.statistics = TrainingStatistics()  # Training
    statistics
119 
120         self.policy_net = self.DQN(self.em.image_tensor_size,
121                                    self.em.num_actions_available()
    ,
122                                    self.include_pick_prediction).
    to(self.device)  # Policy Q Network
123         self.target_net = self.DQN(self.em.image_tensor_size,
124                                    self.em.num_actions_available()
    ,
125                                    self.include_pick_prediction).
    to(self.device)  # Target Q Network
126         self.target_net.load_state_dict(self.policy_net.state_dict
    ())  # Target net has to be the same as policy network
127         self.target_net.eval()  # Target net has to be the same as
     policy network
128         self.optimizer = optim.Adam(params=self.policy_net.
    parameters(), lr=self.lr)  # Q Networks optimizer
129 
130         print("Device: ", self.device)
131 
132     class Agent:
133         """
134         Class that contains all needed methods to control the
    agent through the environment and retrieve information of
135         Its state
136         """
137 
138         def __init__(self, rl_algorithm):
139             """
140 
141             :param self: RLAlgorithm object
142             """
143             self.strategy = rl_algorithm.strategy  # Greedy
    Strategy
144             self.num_actions = rl_algorithm.em.
    num_actions_available()  # Num of actions available
145             self.device = rl_algorithm.device  # Torch device
146             self.rl_algorithm = rl_algorithm
147 
148         def select_action(self, state, policy_net):
149             """
```

```
150             Method used to pick the following action of the robot
151             Method used to pick the following action of the robot
152             :param state: State RLAlgorithm namedtuple with all
    the information of the current state
153             :param policy_net: DQN object used as policy network
    for the RL algorithm
154             :return:
155             """
156             random_action = False
157             if self.rl_algorithm.episode_done:  # If the episode
    has just ended we reset the robot environment
158                 self.rl_algorithm.episode_done = False  # Put the
    variable episode_done back to False
159                 self.rl_algorithm.statistics.new_episode()
160 
161                 self.rl_algorithm.current_action = 'random_state'
     # Return random_state to reset the robot position
162                 self.rl_algorithm.current_action_idx = None
163             else:
164                 rate = self.strategy.get_exploration_rate(
165                     self.rl_algorithm.statistics.current_step)  #
    We get the current epsilon value
166 
167                 if rate > random.random():  # With a probability =
     rate we choose a random action (Explore environment)
168                     action = random.randrange(self.num_actions)
169                     random_action = True
170                 else:  # With a probability = (1 - rate) we
    Explote the information we already have
171                     try:
172                         with torch.no_grad():  # We calculate the
    action using the Policy Q Network
173                             action = policy_net(state.image_raw,
    torch.tensor(
174                                 [[state.coordinate_x, state.
    coordinate_y]], device=self.device),
175                                                 state.
    pick_probability, self.rl_algorithm.include_pick_prediction)\
176                                 .argmax(dim=1).to(self.device)  #
    exploit
177                     except:
178                         print("Ha habido un error")
179 
180                 self.rl_algorithm.current_action = self.
    rl_algorithm.em.actions[action]
181                 self.rl_algorithm.current_action_idx = action
182 
183             return self.rl_algorithm.current_action, random_action
      # We return the action as a string, not as int
```

```
184
185     class DQN(nn.Module):
186         """
187         Class to create a Deep Q Learning Neural Network
188         """
189
190         def __init__(self, image_tensor_size, num_actions,
    include_pick_prediction):
191             """
192
193             :param image_tensor_size: Size of the input tensor
194             :param num_actions: Number of actions, which is the
    output of the Neural Network
195             """
196             super(RLAlgorithm.DQN, self).__init__()
197
198             self.linear1 = nn.Linear(image_tensor_size, int(
    image_tensor_size / 2))
199             self.linear2 = nn.Linear(int(image_tensor_size / 2),
    int(image_tensor_size / 4))
200             extra_features = 2  # coordinates
201             if include_pick_prediction:
202                 extra_features = 3  # pick prediction
203             self.linear3 = nn.Linear(int(image_tensor_size / 4) +
    extra_features, num_actions)
204             self.linear = nn.Linear(image_tensor_size + 2,
    num_actions)
205
206         # Called with either one element to determine next action,
     or a batch
207         # during optimization. Returns tensor([[left0exp,right0exp
    ]...]).
208         def forward(self, image_raw, coordinates, pick_probability
    =None, include_pick_probability=False):
209
210             output = self.linear1(image_raw)
211             output = self.linear2(output)
212             if include_pick_probability:
213                 output = torch.cat((output, coordinates,
    pick_probability), 1)
214             else:
215                 output = torch.cat((output, coordinates), 1)
216             return self.linear3(output)
217
218     class EnvManager:
219         """
220         Class used to manage the RL environment. It is used to
    perform actions such as calculate rewards or retrieve the
221         current state of the robot.
```

```
222         """
223 
224         def __init__(self, rl_algorithm, object_gripped_reward,
    object_not_picked_reward, out_of_limits_reward,
225                      horizontal_movement_reward):
226             """
227             Initialization of an object
228             :param rl_manager: RLAlgorithm object
229             :param object_gripped_reward: Object gripped reward
230             :param object_not_picked_reward: Object not picked
    reward
231             :param out_of_limits_reward: Out of limits reward
232             :param horizontal_movement_reward: Horizontal movement
     reward
233             """
234             self.object_gripped_reward = object_gripped_reward
235             self.out_of_limits_reward = out_of_limits_reward
236             self.object_not_picked_reward =
    object_not_picked_reward
237             self.horizontal_movement_reward =
    horizontal_movement_reward
238 
239             self.device = rl_algorithm.device  # Torch device
240             self.image_controller = ImageController()  #
    ImageController object to manage images
241             self.actions = ['north', 'south', 'east', 'west', '
    pick']  # Possible actions of the objects
242             self.image_height = None  # Retrieved images height
243             self.image_width = None  # Retrieved Images Width
244             self.image = None  # Current image ROS message
245             self.image_tensor = None  # Current image tensor
246             self.pick_probability = None  # Current image tensor
247 
248             self.model_name = 'model-epoch=05-val_loss=0.36-
    weights7y3_unfreeze2.ckpt'
249             # self.model_name = 'resnet50_freezed.ckpt'
250             self.model_family = 'resnet50'
251             self.image_model = ImageModel(model_name=self.
    model_family)
252             self.feature_extraction_model = self.image_model.
    load_model(self.model_name)
253             self.image_tensor_size = self.image_model.
    get_size_features(
254                 self.feature_extraction_model)  # Size of the
    image after performing some transformations
255 
256             self.rl_algorithm = rl_algorithm
257             self.gather_image_state()  # Retrieve initial state
    image
```

```
258
259         def calculate_reward(self, previous_image):
260             """
261             Method used to calculate the reward of the previous
    action and whether it is a final state or not
262             :return: reward, is_final_state
263             """
264             current_coordinates = [self.rl_algorithm.current_state
    .coordinate_x,
265                                    self.rl_algorithm.current_state
    .coordinate_y]  # Retrieve robot's current coordinates
266             object_gripped = self.rl_algorithm.current_state.
    object_gripped  # Retrieve if the robot has an object gripped
267             if Environment.is_terminal_state(current_coordinates,
    object_gripped):  # If is a terminal state
268                 self.rl_algorithm.episode_done = True  # Set the
    episode_done variable to True to end up the episode
269                 episode_done = True
270                 if object_gripped:  # If object_gripped is True,
    the episode has ended successfully
271                     reward = self.object_gripped_reward
272                     self.rl_algorithm.statistics.
    add_succesful_episode(True)  # Saving episode successful
    statistic
273                     self.rl_algorithm.statistics.increment_picks()
      # Increase of the statistics cpunter
274                     rospy.loginfo("Episode ended: Object gripped!"
    )
275                     self.image_controller.record_image(
    previous_image, True)  # Saving the falure state image
276                 else:  # Otherwise the robot has reached the
    limits of the environment
277                     reward = self.out_of_limits_reward
278                     self.rl_algorithm.statistics.
    add_succesful_episode(False)  # Saving episode failure
    statistic
279                     rospy.loginfo("Episode ended: Environment
    limits reached!")
280             else:  # If it is not a Terminal State
281                 episode_done = False
282                 if self.rl_algorithm.current_action == 'pick':  #
    if it is not the first action and action is pick
283                     reward = self.object_not_picked_reward
284                     self.image_controller.record_image(
    previous_image, False)  # Saving the falure state image
285                     self.rl_algorithm.statistics.increment_picks()
      # Increase of the statistics counter
286                 else:  # otherwise
287                     self.rl_algorithm.statistics.
```

```
    fill_coordinates_matrix(current_coordinates)
288                 reward = self.horizontal_movement_reward
289
290             self.rl_algorithm.statistics.add_reward(reward)  # Add
     reward to the algorithm statistics
291             return reward, episode_done
292
293         def gather_image_state(self):
294             """
295             This method gather the relative state of the robot by
    retrieving an image using the image_controller class,
296             which reads the image from the ROS topic specified.
297             """
298             previous_image = self.image
299             self.image, self.image_width, self.image_height = self
    .image_controller.get_image()  # We retrieve state image
300             self.image_tensor, pick_probability = self.
    extract_image_features(self.image)
301             if self.rl_algorithm.include_pick_prediction:
302                 self.pick_probability = pick_probability
303
304             return previous_image
305
306         def extract_image_features(self, image):
307             """
308             Method used to transform the image to extract image
    features by passing it through the image_model CNN
309             network
310             :param image_raw: Image
311             :return:
312             """
313             features, pick_prediction = self.image_model.
    evaluate_image(image, self.feature_extraction_model)
314             features = torch.from_numpy(features)
315             return features.to(self.device), torch.tensor([[math.
    exp(pick_prediction.numpy()[0][1])]]).to(self.device)
316
317         def num_actions_available(self):
318             """
319             Returns the number of actions available
320             :return: Number of actions available
321             """
322             return len(self.actions)
323
324     class EpsilonGreedyStrategy:
325         """
326         Class used to perform the Epsilon greede strategy
327         """
328
```

```
329         def __init__(self, start, end, decay):
330             """
331             Initialization
332             :param start: Greedy strategy epsilon start (
    Probability of random choice)
333             :param end: Greedy strategy minimum epsilon (
    Probability of random choice)
334             :param decay: Greedy strategy epsilon decay (
    Probability decay of random choice)
335             """
336             self.start = start
337             self.end = end
338             self.decay = decay
339 
340         def get_exploration_rate(self, current_step):
341             """
342             It calculates the rate depending on the actual step of
     the execution
343             :param current_step: step of the training
344             :return:
345             """
346             return self.end + (self.start - self.end) * \
347                    math.exp(-1. * current_step * self.decay)
348 
349     class QValues:
350         """
351         It returns the predicted q-values from the policy_net for
    the specific state-action pairs that were passed in.
352         states and actions are the state-action pairs that were
    sampled from replay memory.
353         """
354 
355         @staticmethod
356         def get_current(policy_net, states, coordinates, actions,
    pick_probabilities, include_pick_prediction = False):
357             """
358             With the current state of the policy network, it
    calculates the q_values of
359             :param policy_net: policy network used to decide the
    actions
360             :param states: Set of state images (Preprocessed)
361             :param coordinates: Set of robot coordinates
362             :param actions: Set of taken actions
363             :return:
364             """
365             return policy_net(states, coordinates,
    pick_probabilities, include_pick_prediction).gather(dim=1,
    index=actions.unsqueeze(-1))
366 
```

```
367         @staticmethod
368         def get_next(target_net, next_states, next_coordinates,
    next_pick_probabilities, is_final_state,
    include_pick_prediction = False):
369             """
370             Calculate the maximum q-value predicted by the
    target_net among all possible next actions.
371             If the action has led to a terminal state, next reward
     will be 0. If not, it is calculated using the target
372             net
373             :param target_net: Target Deep Q Network
374             :param next_states: Next states images
375             :param next_coordinates: Next states coordinates
376             :param is_final_state: Tensor indicating whether this
    action has led to a final state or not.
377             :return:
378             """
379             batch_size = next_states.shape[0]  # The batch size is
     taken from next_states shape
380             # q_values is initialized with a zeros tensor of
    batch_size and if there is GPU it is loaded to it
381             q_values = torch.zeros(batch_size).to(torch.device("
    cuda" if torch.cuda.is_available() else "cpu"))
382             non_final_state_locations = (is_final_state == False)
     # Non final state index locations are calculated
383             non_final_states = next_states[
    non_final_state_locations]  # non final state images
384             non_final_coordinates = next_coordinates[
    non_final_state_locations]  # non final coordinates
385             if include_pick_prediction:
386                 non_final_pick_probabilities =
    next_pick_probabilities[non_final_state_locations]  # non final
     pick probabilities
387             else:
388                 non_final_pick_probabilities = None
389             # Max q values of the non final states are calculated
    using the target net
390             q_values[non_final_state_locations] = \
391                 target_net(non_final_states, non_final_coordinates
    , non_final_pick_probabilities, include_pick_prediction).max(
    dim=1)[
392                     0].detach()
393             return q_values
394
395     class ReplayMemory:
396         """
397         Class used to create a Replay Memory for the RL algorithm
398         """
399
```

```
400         def __init__(self, capacity):
401             """
402             Initialization of ReplayMemory
403             :param capacity: Capacity of Replay Memory
404             """
405             self.capacity = capacity
406             self.memory = []  # Actual memory. it will be filled
    with Experience namedtuples
407             self.push_count = 0  # will be used to keep track of
    how many experiences have been added to the memory
408 
409         def push(self, experience):
410             """
411             Method used to fill the Replay Memory with experiences
412             :param experience: Experience namedtuple
413             :return:
414             """
415             if len(self.memory) < self.capacity:  # if memory is
    not full, new experience is appended
416                 self.memory.append(experience)
417             else:  # If its full, we add a new experience and take
     the oldest out
418                 self.memory[self.push_count % self.capacity] =
    experience
419             self.push_count += 1  # we increase the memory counter
420 
421         def sample(self, batch_size):
422             """
423             Returns a random sample of experiences
424             :param batch_size: Number of randomly sampled
    experiences returned
425             :return: random sample of experiences (Experience
    namedtuples)
426             """
427             return random.sample(self.memory, batch_size)
428 
429         def can_provide_sample(self, batch_size):
430             """
431             returns a boolean telling whether or not we can sample
     from memory. Recall that the size of a sample
432             we'll obtain from memory will be equal to the batch
    size we use to train our network.
433             :param batch_size: Batch size to train the network
434             :return: boolean telling whether or not we can sample
    from memory
435             """
436             return len(self.memory) >= batch_size
437 
438     def extract_tensors(self, experiences, include_pick_prediction
```

```
=False):
439         """
440         Converts a batch of Experiences to Experience of batches
    and returns all the elements separately.
441         :param experiences: Batch of Experienc objects
442         :return: A tuple of each element of a Experience
    namedtuple
443         """
444         batch = Experience(*zip(*experiences))
445 
446         states = torch.cat(batch.state)
447         actions = torch.cat(batch.action)
448         rewards = torch.cat(batch.reward)
449         next_states = torch.cat(batch.next_state)
450         coordinates = torch.cat(batch.coordinates)
451         next_coordinates = torch.cat(batch.next_coordinates)
452         if include_pick_prediction:
453             pick_probabilities = torch.cat(batch.pick_probability)
454             next_pick_probabilities = torch.cat(batch.
    next_pick_probability)
455         else:
456             pick_probabilities = None
457             next_pick_probabilities = None
458         is_final_state = torch.cat(batch.is_final_state)
459 
460         return states, coordinates, pick_probabilities, actions,
    rewards, next_states, next_coordinates, \
461                next_pick_probabilities, is_final_state
462 
463     @staticmethod
464     def saving_name(batch_size, gamma, eps_start, eps_end,
    eps_decay, lr, others=''):
465         return 'bs{}_g{}_es{}_ee{}_ed{}_lr_{}_{}.pkl'.format(
466             batch_size, gamma, eps_start, eps_end, eps_decay, lr,
    others
467         )
468 
469     def save_training(self, dir='trainings/', others='optimal'):
470 
471         filename = self.saving_name(self.batch_size, self.gamma,
    self.eps_start, self.eps_end, self.eps_decay, self.lr,
472                                     self.save_training_others)
473 
474         def create_if_not_exist(filename, dir):
475             current_path = os.path.dirname(os.path.realpath(
    __file__))
476             filename = os.path.join(current_path, dir, filename)
477             if not os.path.exists(os.path.dirname(filename)):
478                 try:
```

```
479                     os.makedirs(os.path.dirname(filename))
480                 except OSError as exc:  # Guard against race
    condition
481                     if exc.errno != errno.EEXIST:
482                         raise
483             return filename
484 
485         rospy.loginfo("Saving training...")
486 
487         abs_filename = create_if_not_exist(filename, dir)
488 
489         self.em.image_model = None
490         self.em.feature_extraction_model = None
491 
492         with open(abs_filename, 'wb+') as output:  # Overwrites
    any existing file.
493             pickle.dump(self, output, pickle.HIGHEST_PROTOCOL)
494 
495         rospy.loginfo("Saving Statistics...")
496         print(filename)
497 
498         filename = 'trainings/{}_stats.pkl'.format(filename.split(
    '.pkl')[0])
499         self.statistics.save(filename=filename)
500 
501         rospy.loginfo("Training saved!")
502 
503     @staticmethod
504     def recover_training(batch_size=32, gamma=0.999, eps_start=1,
    eps_end=0.01,
505                          eps_decay=0.0005, lr=0.001,
    include_pick_prediction=False, others='optimal', dir='trainings
    /', ):
506         current_path = os.path.dirname(os.path.realpath(__file__))
507         filename = RLAlgorithm.saving_name(batch_size, gamma,
    eps_start, eps_end, eps_decay, lr, others)
508         filename = os.path.join(current_path, dir, filename)
509         try:
510             with open(filename, 'rb') as input:
511                 rl_algorithm = pickle.load(input)
512                 rospy.loginfo("Training recovered. Next step will
    be step number {}"
513                               .format(rl_algorithm.statistics.
    current_step))
514 
515                 rl_algorithm.em.image_model = ImageModel(
    model_name=rl_algorithm.em.model_family)
516                 rl_algorithm.em.feature_extraction_model =
    rl_algorithm.em.image_model.load_model(
```

```
517                     rl_algorithm.em.model_name)
518
519                 return rl_algorithm
520         except IOError:
521             rospy.loginfo("There is no Training saved. New object has been created")
522             return RLAlgorithm(batch_size=batch_size, gamma=gamma, eps_start=eps_start, eps_end=eps_end,
523                                eps_decay=eps_decay, lr=lr, include_pick_prediction=include_pick_prediction, save_training_others=others)
524
525     def train_net(self):
526         """
527         Method used to train both the train and target Deep Q Networks. We train the network minimizing the loss between
528         the current Q-values of the action-state tuples and the target Q-values. Target Q-values are calculated using
529         thew Bellman's equation:
530
531         q*(state, action) = Reward + gamma * max( q*(next_state, next_action) )
532         :return:
533         """
534         # If there are at least as much experiences stored as the batch size
535         if self.memory.can_provide_sample(self.batch_size):
536             experiences = self.memory.sample(self.batch_size)  # Retrieve the experiences
537             # We split the batch of experience into different tensors
538             states, coordinates, pick_probabilities, actions, rewards, next_states, next_coordinates, \
539                 next_pick_probabilities, is_final_state = self.extract_tensors(experiences, self.include_pick_prediction)
540             # To compute the loss, current_q_values and target_q_values have to be calculated
541             current_q_values = self.QValues.get_current(self.policy_net, states, coordinates, actions,
542
543 pick_probabilities, self.include_pick_prediction)
544             # next_q_values is the maximum Q-value of each future state
545             next_q_values = self.QValues.get_next(self.target_net, next_states, next_coordinates,
546
547 next_pick_probabilities, is_final_state, self.include_pick_prediction)
548             target_q_values = (next_q_values * self.gamma) +
```

```
    rewards
547
548             loss = F.mse_loss(current_q_values, target_q_values.
    unsqueeze(1))  # Loss is calculated
549             self.optimizer.zero_grad()  # set all the gradients to
     0 (initialization) so that we don't accumulate
550             # gradient throughout all the backpropagation
551             loss.backward(
552                 retain_graph=True)  # Compute the gradient of the
    loss with respect to all the weights and biases in the
553             # policy net
554             self.optimizer.step()  # Updates the weights and
    biases with the gradients computed
555
556         if self.statistics.episode % self.target_update == 0:  #
    If target_net has to be updated in this episode
557             self.target_net.load_state_dict(self.policy_net.
    state_dict())  # Target net is updated
558
559     def next_training_step(self, current_coordinates,
    object_gripped):
560         """
561         This method implements the Reinforcement Learning
    algorithm to control the UR3 robot.  As the algorithm is
    prepared
562         to be executed in real life, rewards and final states
    cannot be received until the action is finished, which is the
563         beginning of next loop. Therefore, during an execution of
    this function, an action will be calculated and the
564         previous action, its reward and its final state will be
    stored in the replay memory.
565         :param current_coordinates: Tuple of float indicating
    current coordinates of the robot
566         :param object_gripped: Boolean indicating whether or not
    ann object has been gripped
567         :return: action taken
568         """
569         self.statistics.new_step()  # Add new steps statistics
570         self.previous_state = self.current_state  # Previous state
     information to store in the Replay Memory
571         previous_action = self.current_action  # Previous action
    to store in the Replay Memory
572         previous_action_idx = self.current_action_idx  # Previous
    action index to store in the Replay Memory
573         previous_image = self.em.gather_image_state()  # Gathers
    current state image
574
575         self.current_state = State(current_coordinates[0],
    current_coordinates[1], self.em.pick_probability,
```

```
576                                     object_gripped, self.em.
    image_tensor)  # Updates current_state
577
578         # Calculates previous action reward an establish whether
    the current state is terminal or not
579         previous_reward, is_final_state = self.em.calculate_reward
    (previous_image)
580         action, random_action = self.agent.select_action(self.
    current_state,
581                                                          self.
    policy_net)  # Calculates action
582
583         # There are some defined rules that the next action have
    to accomplish depending on the previous action
584         action_ok = False
585         while not action_ok:
586             # Its forbidden to perform two cosecutive pick actions
     in the same place
587             if action == 'pick' and previous_action != 'pick':
588                 action_ok = True
589             # If previous action was south, it is forbidden to
    perform a 'north' action for
590             # The robot not to go back to the original position.
591             elif action == 'north' and previous_action != 'south':
592                 action_ok = True
593             # If previous action was north, it is forbidden to
    perform a 'south' action for
594             # The robot not to go back to the original position.
595             elif action == 'south' and previous_action != 'north':
596                 action_ok = True
597             # If previous action was east, it is forbidden to
    perform a 'west' action for
598             # The robot not to go back to the original position.
599             elif action == 'west' and previous_action != 'east':
600                 action_ok = True
601             # If previous action was west, it is forbidden to
    perform a 'east' action for
602             # The robot not to go back to the original position.
603             elif action == 'east' and previous_action != 'west':
604                 action_ok = True
605             elif action == 'random_state':
606                 action_ok = True
607             else:
608                 action, random_action = self.agent.select_action(
    self.current_state,
609
    self.policy_net)  # Calculates action
610
611         if random_action:
```

```
612             self.statistics.random_action()  # Recolecting
    statistics
613
614         # Random_state actions are used just to initialize the
    environment to a random position, so it is not taken into
615         # account while storing state information in the Replay
    Memory.
616         # If previous action was a random_state and it is not the
    first step of the training
617         if previous_action != 'random_state' and self.statistics.
    current_step > 1:
618             self.memory.push(  # Pushing experience to Replay
    Memory
619                 Experience(  # Using an Experience namedtuple
620                     self.previous_state.image_raw,  # Initial
    state image
621                     torch.tensor([[self.previous_state.
    coordinate_x, self.previous_state.coordinate_y]],
622                                  device=self.device),  # Initial
    coordinates
623                     self.previous_state.pick_probability,
624                     torch.tensor([previous_action_idx], device=
    self.device),  # Action taken
625                     self.current_state.image_raw,  # Final state
    image
626                     torch.tensor([[self.current_state.coordinate_x
    ,
627                                    self.current_state.coordinate_y
    ]],
628                                  device=self.device),  # Final
    coordinates
629                     self.current_state.pick_probability,
630                     torch.tensor([previous_reward], device=self.
    device),  # Action reward
631                     torch.tensor([is_final_state], device=self.
    device)  # Episode ended
632                 ))
633
634             # Logging information
635             rospy.loginfo("Step: {}, Episode: {}, Previous reward:
     {}, Previous action: {}".format(
636                 self.statistics.current_step - 1,
637                 self.statistics.episode,
638                 previous_reward,
639                 previous_action))
640
641             self.train_net()  # Both policy and target networks
    gets trained
642
```

```
643         return action
```

.2.3 Environment.py

```
1 """
2 This class defines a RL environment for a pick and place task with
      a UR3 robot.
3 This environment is defined by its center (both cartesian and
     angular coordinates), the total length of its x and y axis
4 and other parameters
5 """
6
7 import random
8 from BlobDetector.BlobDetector import BlobDetector
9 from ai_manager.ImageController import ImageController
10 from math import floor
11
12
13 class Environment:
14     X_LENGTH = 0.175  # Total length of the x axis environment in
     meters
15     Y_LENGTH = 0.225  # Total length of the y axis environment in
     meters
16
17     CAMERA_SECURITY_MARGIN = 0.035  # As the camera is really
     close to the gripping point, it needs  a security marging
18     X_LIMIT = X_LENGTH - CAMERA_SECURITY_MARGIN  # Robot
     boundaries of movement in axis X
19     Y_LIMIT = Y_LENGTH - CAMERA_SECURITY_MARGIN  # Robot
     boundaries of movement in axis Y
20
21     CARTESIAN_CENTER = [-0.31899288568, -0.00357907370787,
     0.376611799631]  # Cartesian center of the RL environment
22     ANGULAR_CENTER = [2.7776150703430176, -1.5684941450702112,
     1.299912452697754, -1.3755658308612269,
23                       -1.5422008673297327, -0.3250663916217249]  #
      Angular center of the RL environment
24     PLACE_CARTESIAN_CENTER = [0, 0.25, CARTESIAN_CENTER[2]]  #
     Cartesian center of the place box
25     ANGULAR_PICTURE_PLACE = [1.615200161933899,
     -1.235102955495016, 0.739865779876709, -1.2438910643206995,
     -1.5095704237567347, -0.06187755266298467]
26
27     PICK_DISTANCE = 0.01  # Distance to the object when the robot
     is performing the pick and place action
28     ACTION_DISTANCE = 0.02  # Distance to the object when the
     robot is performing the pick and place action
29
```

```
30      ENV_BOUNDS_TOLERANCE = 0
31
32      @staticmethod
33      def generate_random_state(image=None, strategy='ncc'):
34          """
35          Calculates random coordinates inside the Relative
    Environment defined.
36          To help the robot empty the box, the generated coordinates
     won't be in the center of the box, because this is
37          the most reachable place of the box.
38
39          :param strategy: strategy used to calculate random_state
    coordinates
40          :return:
41          """
42          def generate_random_coordinates():
43              coordinate_x = random.uniform((-Environment.X_LIMIT +
    Environment.ENV_BOUNDS_TOLERANCE) / 2,
44                                            (Environment.X_LIMIT -
    Environment.ENV_BOUNDS_TOLERANCE) / 2)
45              coordinate_y = random.uniform((-Environment.Y_LIMIT +
    Environment.ENV_BOUNDS_TOLERANCE) / 2,
46                                            (Environment.Y_LIMIT -
    Environment.ENV_BOUNDS_TOLERANCE) / 2)
47              return coordinate_x, coordinate_y
48
49          # Random coordinates avoiding the ones in the center,
    which have a bigger probability of being reached by the
50          # robot.
51          if strategy == 'ncc' or strategy == '
    non_centered_coordinates':
52              coordinates_in_center = True
53              while coordinates_in_center:
54                  coordinate_x, coordinate_y =
    generate_random_coordinates()
55                  if abs(coordinate_x) > (Environment.X_LIMIT / 4)
    or abs(coordinate_y) > (Environment.Y_LIMIT / 4):
56                      coordinates_in_center = False
57          elif strategy == 'optimal' and image is not None:  #
    Before going to a random state, we check that there are pieces
    in this place
58              blob_detector = BlobDetector(x_length=Environment.
    X_LENGTH, y_length=Environment.Y_LENGTH, columns=4, rows=4)
59              optimal_quadrant = blob_detector.find_optimal_quadrant
    (image)
60              optimal_point = blob_detector.quadrants_center[
    optimal_quadrant]
61
62              coordinate_x = optimal_point[0] * 0.056
```

```
63              coordinate_y = optimal_point[1] * 0.056
64          else: # Totally random coordinates
65              coordinate_x, coordinate_y =
    generate_random_coordinates()
66
67          return [coordinate_x, coordinate_y]
68
69      @staticmethod
70      def get_relative_corner(corner):
71          """
72          Function used to calculate the coordinates of the
    environment corners relative to the CARTESIAN_CENTER.
73
74          :param corner: it indicates the corner that we want to get
     the coordinates. It' s composed by two letters
75          that indicate the cardinality. For example: ne indicates
    North-East corner
76          :return coordinate_x, coordinate_y:
77          """
78          if corner == 'sw' or corner == 'ws':
79              return -Environment.X_LIMIT / 2, Environment.Y_LIMIT /
     2
80          if corner == 'nw' or corner == 'wn':
81              return Environment.X_LIMIT / 2, Environment.Y_LIMIT /
    2
82          if corner == 'ne' or corner == 'en':
83              return Environment.X_LIMIT / 2, -Environment.Y_LIMIT /
     2
84          if corner == 'se' or corner == 'es':
85              return -Environment.X_LIMIT / 2, -Environment.Y_LIMIT
    / 2
86
87      @staticmethod
88      def is_terminal_state(coordinates, object_gripped):
89          """
90          Function used to determine if the current state of the
    robot is terminal or not
91          :return: bool
92          """
93          def get_limits(length): return length / 2 - Environment.
    ENV_BOUNDS_TOLERANCE  # functon to calculate the box boundaries
94          x_limit_reached = abs(coordinates[0]) > get_limits(
    Environment.X_LIMIT)  # x boundary reached
95          y_limit_reached = abs(coordinates[1]) > get_limits(
    Environment.Y_LIMIT)  # y boundary reached
96          return x_limit_reached or y_limit_reached or
    object_gripped # If one or both or the boundaries are reached
    --> terminal state
```

.2.4 ImageController.py

```
#!/usr/bin/env python
# coding: utf-8

import os
import time

import rospy
from PIL import Image as PILImage
from sensor_msgs.msg import Image

"""
This class is used to manage sensor_msgs Images.
"""

class ImageController:
    def __init__(self, path=os.path.dirname(os.path.realpath(__file__)), image_topic='/usb_cam/image_raw'):
        self.ind_saved_images = 0  # Index which will tell us the number of images that have been saved
        self.success_path = "{}/success".format(path)  # Path where the images are going to be saved
        self.fail_path = "{}/fail".format(path)  # Path where the images are going to be saved
        self.image_topic = image_topic

        # If it does not exist, we create the path folder in our workspace
        try:
            os.stat(self.success_path)
        except:
            os.mkdir(self.success_path)

        # If it does not exist, we create the path folder in our workspace
        try:
            os.stat(self.fail_path)
        except:
            os.mkdir(self.fail_path)

    def get_image(self):
        msg = rospy.wait_for_message(self.image_topic, Image)

        return self.to_pil(msg), msg.width, msg.height

    def record_image(self, img, success):
        path = self.success_path if success else self.fail_path  # The path were we want to save the image is
```

```
41
42          image_path = '{}/img{}.png'.format(  # Saving image
43              path,  # Path
44              time.time())  # FIFO queue
45
46          img.save(image_path)
47
48          self.ind_saved_images += 1  # Index increment
49
50      def to_pil(self, msg, display=False):
51          size = (msg.width, msg.height)  # Image size
52          img = PILImage.frombytes('RGB', size, msg.data)  #
    sensor_msg to Image
53          return img
54
55  if __name__ == '__main__':
56      rospy.init_node('image_recorder')  # ROS node initialization
57      image_controller = ImageController(path='/home/pilar/Pilar/
    ros_pictures', image_topic='/usb_cam2/image_raw')
58      img, width, height = image_controller.get_image()
59      image_controller.record_image(img, True)
```

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