A Real Framework to Apply Collaborative Robots in Upper Limb Rehabilitation

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Abstract: Rehabilitation is an important recovery process from dysfunctions that improves the patient's activities of daily living. On the other hand, collaborative robotic applications, where humans and machines can share the same space, are increasing once it allows splitting a task between the accuracy of a robot and the ability and flexibility of a human. This paper describes an innovative approach that uses a collaborative robot to support the rehabilitation of the upper limb of patients, complemented by an intelligent system that learns and adapts its behaviour according to the patient's performance during the therapy. This intelligent system implements the reinforcement learning algorithm, which makes the system robust and independent of the path of motion. The validation of the proposed approach uses a UR3 collaborative robot training in a real environment. The main control is the resistance force that the robot is able to do against the movement performed by the human arm.

1 INTRODUCTION

According to the World Health Organization, the number of people that live with disability had increased by 17 million between 2005 and 2015. About 74% is linked to health conditions where the patient could benefit from rehabilitation (Gimigliano and Negrini, 2017). It is mainly focused on the elderly population as a risk group of cardiovascular and respiratory diseases. The population of the world aged 60 years and over is set to increase from 841 million in 2013 to more than 2 billion in 2050, according to (Chatterji et al., 2015). In this way, the rehabilitation process is of huge importance to society.

This paper demonstrates how a collaborative robot can help patients with non-paralysing dysfunctions of upper limbs. The proposed system is based on the collaborative robot UR3 from Universal Robots© and on the control of the force applied to the movement by using a self control algorithm based on the Reinforcement Learning (RL) approach. The UR3 end-effector is equipped with a force sensor that provides the data about the movement performed by the patient.

The self control algorithm is implemented in Python to communicate with the collaborative robot. It is noted in (Toth et al., 2005) that a long time is wasted in the set up of the system for each patient and exercise. This time can be decreased using the autonomous control algorithm because it is adaptable to patient needs (force) on a free trajectory, i.e., the therapist may indicate any path to the patient without having to configure the movement on the robot and, when there is a realisation of the motion, the autonomous algorithm gives the resistance force independently of the exercise's directions.

This work presents the results through the realization of an experiment of the system with a healthy patient. This experiment was divided in two parts: the first considering the training only in one axis and second in the three Cartesian axes. The data about the movement, such as the applied force by the human arm on the UR3, the resistance provided by the

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robot on the motion, the velocity and position of the end-effector and the rewards obtained using the self control are presented.

The rest of this paper is organized as follows. Section 2 presents the related work on rehabilitation using automatic devices, e.g., robots. Section 3 describes the development of the simulation and real robot interface and the algorithms to analyze the patient performance and the self-control module. Section 4 discuses the obtained results both in simulation and real robot. Finally, Section 5 presents some conclusions regarding this problem and points out future works.

2 RELATED WORK

Industrial robotic arms are not unique to manufacturing processes on a shop-floor, with the emergence of the human-robot interaction concept demonstrated by (Toth et al., 2004), it is possible to develop robotic applications that exercise patients with upper limb trauma. The effectiveness of this system and the safety processes developed to avoid further injury to patients are presented in (Toth et al., 2005), where it is evident that the point of most interest in these applications is the control system.

During physical therapy movements the patient needs a force opposite to his/her movement to have an evolution of his/her clinical condition, (Gijbels et al., 2011) through a mechanical spring system (The Armeo Spring) compares different coefficients for over weeks of treatment. With resistance to movement during physical therapy, multiple sclerosis patients have achieved improvements in the treatment of upper limb muscle strength. Other work with Armeo Spring is shown by (Cortés et al., 2014), where a model of an upper limb integrate into Virtual Reality (VR) is applied. The propose of work is to establish a method to estimate the posture of the human limb attached to the exoskeleton. The joint angle measurements and the constraints of the exoskeleton are used to estimate the human limb joint angle in VR. The simulation was performed in the V-REP platform and signals were measured direct from Armeo. For upper limb rehabilitation by exoskeleton-guided movement methods, the state of the art from (Tejima, 2001; Lo and Xie, 2012) lists the main developments, contributions, and future research for the sector.

In recent years collaborative robotic arms have emerged as a strong ally in human-robotics interaction, whether in domestic, industrial, academic and clinical applications. This type of robot, when employed in patient's rehabilitation situations, requires a certain infrastructure, described by (Malosio et al., 2010). The system architecture that assists patients in motor recovery consists of a central control element, actuators, sensors, and algorithms. In this way, collaborative robots, besides helping people with upper limb difficulties to perform daily tasks (Maheu et al., 2011), can also contribute to motor rehabilitation when well configured.

Using a 7 Degrees of Freedom (DoF) KUKA robot, (Papaleo et al., 2013) describes the development of a patient-tailored system, that is, the system is capable of adapting to patient interactions through sensing installed in conjunction with the robot. With this tool, it is possible to assist patients in Activities of Daily Living (ADLs) by encouraging them to use their residual capabilities through the process of monitoring their performance, either by 3D or 2D motion.

When monitoring a patient's performance while executing the task, it is recommended that the system be provided by learning by observation, ie the system should have the Interactive Learning Control (ILC) technique (Realmuto et al., 2016). Thus, the implementation of the proposed system can be updated during the patient's evolution. This process is important for the patient to have evolution during the ever increasing rehabilitation. The usage of systems that have to train by supervised learning is shown by the Universal RoboTrainer project (Weigelin et al., 2018). It is used the advantage of collaborative robots to improve the rehabilitation of his/her patients. This project uses a model from Universal Robot to train disabled upper limbs, where the main idea is based on studies that prove the effectiveness of repetitive movements in the treatment of dysfunctions. Some tests with this device have been performed in real cases. One of them addresses the confidence in the medical human-robot iterations, and presents the main issues in that approach on the patient side, as signs of distress in the exercises, concern, and expectation about the movements attached to a robot arm, and others.

The aforementioned works are fundamental for the proposed approach in developing a skillful framework to support patients in upper limb rehabilitation with collaborative robots. Each of them demonstrates the key points for the development of our system, thus these points are described in more detail in future sessions.

3 SYSTEM ARCHITECTURE

In order to rehabilitate patients with problems due to ADLs, the first step was the development of the system architecture shown in Figure 1, composed of hardware, to unite all parts of the system and use its functions, together with software architecture and an application procedure developed in python.

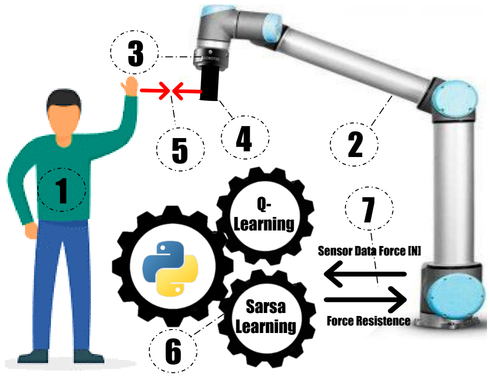


Figure 1: System Architecture of proposed approach.

The point numbers in Figure 1 represent each part of the system, (1) the user who interacts with the robot by moving his arm, resulting in the application of forces on different Cartesian axes (X, Y, Z) acting on the robot tool. In (2) is the robot itself, which is a collaborative manipulator. This manipulator is equipped with a force-torque sensor FT-300 (3), capable of measuring force in the X, Y and Z directions of the Cartesian plane. Coupled to the force sensor (4) is a cone-shaped 3D printed tool that the user can hold and perform movements with the robot. This printed piece has high rigidity, able to withstand the force exerted by the user on the robot, this iteration of forces between the robot and the user is represented by (5). Then, (6) represents RL algorithms ("Q-learning" and "SARSA Learning") which, depending on the movement performed by the human, will adjust the resistance to movement ("force Resistance") using the data measured with the force sensor ("Sensor Data Force (N)") linked to the rehabilitation manipulator. Finally, (7) indicates Modbus TCP communication between the robot and the computer running the python application. The robot sends the force data applied to all axes, which is processed by the program, which returns the resistance force that the robot will apply in the iteration with the user.

3.1 Mechanical Description

The developed application is composed by several components. The manipulator robot that reacts to the forces applied by the user refers to a Universal Robots UR3 collaborative robot. It is a small collaborative tabletop robot for light assembly tasks and automated workbench scenarios, equipped with a control box and a programming user interface. The robot weighs 11 kg, with a payload of 3 kg, 360-degree rotation on all wrist joints, and infinite rotation on end joint. These unique features make UR3 a flexible, lightweight, collaborative table-top robot to work side-by-side with humans in a safe way.

Table 1: Specifications of the FT300 force-torque sensor.

Feature	Value	Unit
Measure Range FX, FY, FZ	+/- 300	N
Measure Range MX, MY, MZ	+/- 30	N.m
Data Output Rate	100	Hz
Weight	0.3	Kg

The UR3 robot is equipped with a force-torque sensor FT300 of 6 DoF. However, only three DoFs were processed for this work: the force on the X, Y and Z axis to measure the force of human during the procedure of interacting with the robot. Table 1 presents the specifications of this sensor. The data FX, FY and FZ represents the measure of force in each direction. The variables MX, MY and MZ are the moments that can be measured.

3.2 Self Control Model Description

The robotic system has to provide force training to help the improvement of the musculoskeletal structure. Resistance force is applied to the motion of the patient arm. If the executed force by the human was always constant, it would only be necessary to set a resistance force proportional to this value to ensure that the arm performs a higher force, fulfilling the objective. However, once the system is dynamic, some control is necessary to set that resistance force according to the human arm force.

Another rehabilitation systems found in literature develop their control in other ways, as presented as an example in (Toth et al., 2005). In most cases, larger periods (time) are wasted to set up the system to each patient. Therefore, to improve the usability and facility was implemented a self-control based on the RL technique, and it is a method in which the robotic system uses information gathered from the environment to learn the best action to take.

When the system is active, the robotic arm can recognize the force of the patient and change its joint torque values, making them responsible, in real-time, by itself and adaptable to any patient. The premise of the system is to work with the patients that are capable of performing some upper limb motion, therefore the biofeedback will be the force performed in this movement. No pre-programmed path planning is required on the robot's side, but the therapists shall indicate to the patient which are the motions for that treatment section.

The RL algorithm used to built the self control is called SARSA. The concept and functionality of this control algorithm are best explained in (Sutton and Barto, 2018; Lewis and Vrabie, 2009; Wiering and Van Otterlo, 2012). The SARSA algorithm is constructed to make a decision in a dynamic process and to adapt the next choice to the environment. It is worth remembering that the RL systems are used to solve the Markov Decision Process (MDP) (Sutton and Barto, 2018).

The MDP is a framework that guides a decision in a dynamic process. Explaining quickly the environment on an MDP is separated in states and actions. The states represent each system setting (this setting can be the value of position, speed, angle, force, or otherwise). Actions are the dynamic process that drives the system from one specific state to another (this dynamic process can be understood as changing the variables represented by states). Applied to the rehabilitation problem, the states to be understood are all forces performed by the human arm. The actions are represented by the possible decisions that the system can make. Working with the resistance force, the decisions are: increase the force performed on the end-effector, decrease or hold the same variable.

The goal of self-control is to choose the best decision based on the system's current state. However, as this behavior is not known at first, the method of trial-and-error is performed. Initially, the system starts in some state s_x, makes a decision (some action a_x is performed), goes to another different state s_y, and based on this new state, chooses the new action a_y. When the system act in the environment some feedback signal is collected. This value is used to evaluate the action a_x in the certain state s_x. So, if the action results in an expected state (considered positive for the system) the algorithm awards a positive reward r_x to the set "previous state - action - next state", else the reward is negative to the same set. The attribution of positive rewards is linked, in this case, to the resistance force made by the robot that guides the patient to perform the expected arm strength in that physiotherapy session.

The rewards are used to calculate the Q-matrix, which relates the states with the actions. For SARSA technique the Q-matrix is updated using the Equation 1. Note that on the updating are used: s_x, a_x, r_x, s_y, and a_y. As the system uses the pair (s_y, a_y) is possible to evaluate if the current action a_x will generate the next better action a_y.

$$Q(s_x,a_x) \leftarrow Q(s_x,a_x) + \alpha(\left[r_x + \gamma Q(s_y,a_y) - Q(s_x,a_x)\right]) \tag{1}$$

Therefore, if an action a_x in the state s_x gets many positive rewards, the Q-matrix value corresponding to this pair (state, action) will be greater than the other actions for the same state. Therefore, this pair (s_x,a_x) will always be chosen in further similar decisions. The constants α and γ are called learning rates and both are values in the range [0,1]. These values are used because the system could perform a pair (s_x,a_x) that results in a positive reward, but it is not a better solution. Thus, to ensure that values that appear correct do not increase very quickly, the system uses these variables as a discount. There is no method for calculating these values, but if they are too small the system will take longer to converge, and if they are too close to 1 the system will be more likely to get stuck at a local maximum.

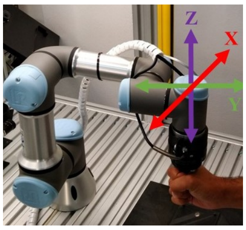
An essential concept used in this approach are the episodes (the set of iterations that comprehend a motion of the human arm in period of time). In other words, a single episode corresponds to all the measurements performed by the robot during 0.2 seconds (15 iterations).

To ensure that the system will always measure a real value without a possible measured noise (due to the changing movement direction), an average measurement based on the episode is configured. For this reason, each measurement presented on the Section 4 represents a set of 15 interactions within the environment.

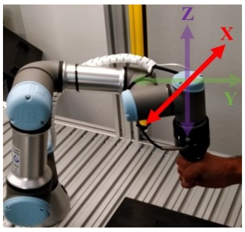
3.3 Real Robot Interaction

The interaction between the human and the robot will be divided into two moments. At first, it was requested to the patient to move the robot only along the x-axis. To help the patient to accomplish the proposed movement, the UR3 was configured also to move in the same axis that is represented by the red arrow in Figure 2b. When the patient starts the motion, the sensor starts measuring and this data is used to feed the RL technique. After that, it was requested for the patient to move the robot in any direction, in other words, the human can move the robot along the three Cartesian axes that are displayed in Figures 2b, 2c and 2d. This makes the decision of the system much more complex because the robot should deliver the resistance force in three axes and none of them can interfere in another.

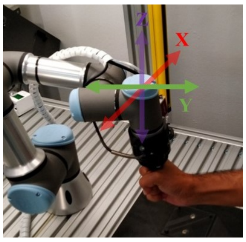
Note that on both stages of the experiment the patient tried to execute a movement with a constant velocity. The robot at both moments is set to never change the angle of the end-effector as this could cause calculation errors on the side of the control algorithm. Another set up in the UR3 is that all the motions start from a home position, exemplified in Figure 2a. Before the movement begins, the force sensor attached to the robot is re-calibrated to avoid errors in the measurements.



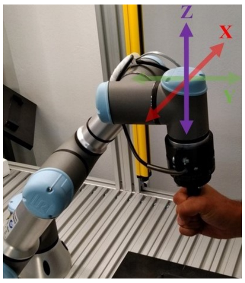
(a) Home position.



(b) Axis X.



(c) Axis Y.



(d) Axis Z

Figure 2: Images that show the motions along the three Cartesian axes.

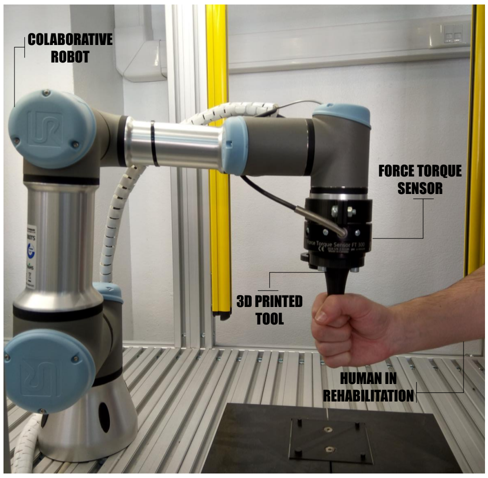


Figure 3: Force training with the patient.

4 RESULTS

The results are measured using the RL algorithm as the self-control model applied in the UR3 to training with a healthy person. The patient has 23 years old, 1,92 meters, and 0.81 meters of arm's length. The set up of the experiment is: the individual stands in front of the robot, grabs the UR3's end-effector as shown by Figure 3, and moves the robot along a path stipulated by the experiment therapist.

The experiment goal is to train the algorithm to provide a resistance force according to the patient needs in both cases. Therefore, the results presented in this section will be divided into two parts, the one axis, and the three axes experiment, respectively.

4.1 The One Axis Experiment

This part refers to the first iteration of the intelligent system with the patient arm. The system records the values of the movement provided by sensors and robots. The first variable shown in Figure 4 is the velocity of the UR3's end-effector. It is expected that the velocity stands around value and it seems to happen during all training for the two algorithms. The value of this velocity is 150 mm/s and the variation between the negative and positive value occurs due to the changing of direction of movement. It is also noticed some overtaking in the velocity's curve. This may occur due to measurement errors or the motion changing.

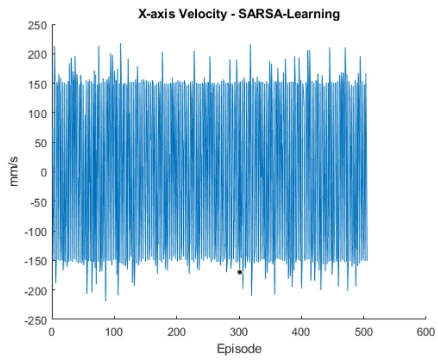


Figure 4: Recorded velocity on the movement.

Another variable is the end-effector position. As the behavior is independent of the trajectory, this curve is not always well defined and it is presented in Figure 5.

Even disregarding the trajectory, some movement patterns can be noticed due to the UR3 characteristics. This fact is explained by the curve generated in Figure 4 resembling the resistance force values provided by the UR3 manual. To analyze how this value changes and when this happens, the Figure 6 shows the comparison between the curves. Note that it is presented a set of episodes to facilitate the reading of the data.

The behavior expected is again noticed. The position curve represents the force direction measured by sensor. This means that the resistance force applied by the UR3 robot should be the same behavior, but on the opposite way. The UR3's force showed in

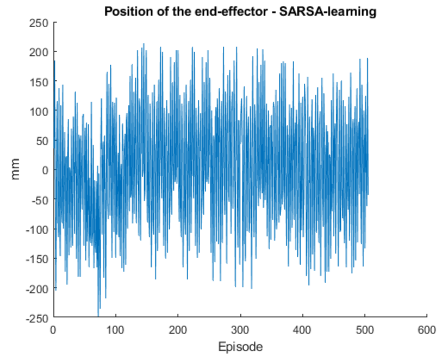


Figure 5: Recorded position on the movement.

Figure 6 is calculated by the self-control using as an input the measured resultant force by the sensor. It is also considered as a goal of the system, that the same variable is around the value of 25 N, inside a proposed range (20 N - 40 N). The system cannot guarantee that the forces are always inside the proposed range, however, most times has to seek this target. The Figure 7 shows this data to the entire training. Notice that the data represents the force measured in the three axes (XYZ). Even that motion is only in one axis, there are reading forces in all axes and these variables should be considered.

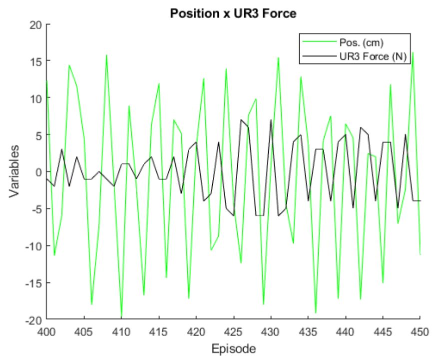


Figure 6: Comparison between position and resistance force.

Figure 7 presents many values that exceed the 40 N. Some of these values can be considering that the patient can execute this force for a short period (time). However, this value not always represents reality. Even with the technique used to mitigate the reading errors, some of them were detected, principally when the patient changes the direction of the movement. Therefore, the analysis must be done considering the average value of the force, which seems to be around 28 N, and this is acceptable behavior. This overtakes are also a result of the force applied in the other axes recorded by the sensor. Thus, if the forces on the other directions were disregarded, the force should perform better.

Figure 7: The measured resultant force by the sensor.

Figure 8 presents the force for the measurements about the x-axis. The value of the force depends on the direction of the movement. So, the reading of this variable should only be considered the value module. However, this curve also shows to the reader that the systems choose the next resistance force independently of the direction, promoting an almost constant variation in the x-axis force.

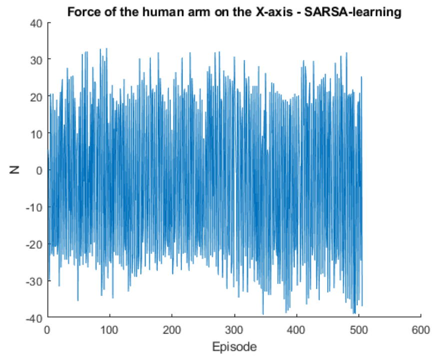


Figure 8: The measured force by the sensor on the x-axis.

The system seeks for actions (inside the proposed set of actions) that are correct just for some specific situations. It is expected that the self-control chooses these correct actions to get the rewards and at the end of training the negative be smaller than the positive. This objective is reached and the Figure 9 shows a comparison between the number of positive (+1) and negative (-1) rewards assigned. The number of positive rewards, where the system recorded a human arm force inside the proposed range, is at least two times larger than the negative rewards.

The goal pursued was successfully achieved, precisely because the force of the human arm remained around the force established during almost all training. However, it is not clear what is the better resistance force that the robot should deliver to the patient in each episode. The data recorded on the selected force shows exactly this situation, as stressed in Fig-

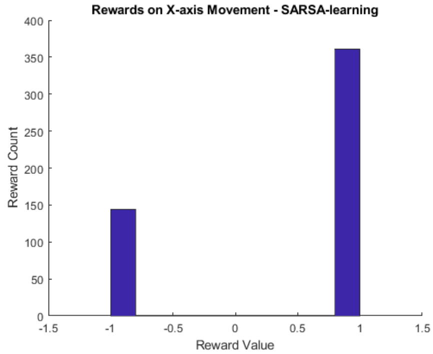


Figure 9: Rewards assigned by the SARSA algorithm.

ure 10. Nevertheless is possible to analyze that the robot didn't learn the better force, but the learning was the best moments to increase or decrease the force.

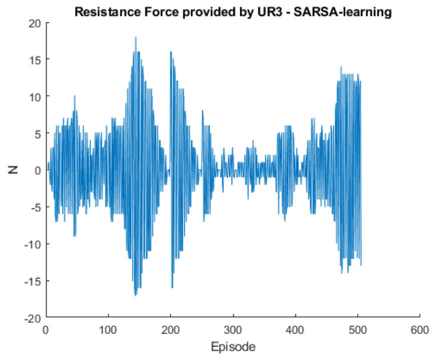


Figure 10: The UR3's applied force.

It was noticed that empirically an UR3 force of 6 N is capable to ensure that the arm will execute a force close to expected, but this value depends on the position of the patient relative to the robot. Thus, sometimes a smaller or higher resistance force is required to accomplish the goals. As the system is dynamic and complex, 500 interactions were not enough to make the system to fit optimally, but it is possible to verify that this same number of episodes was enough for the robot to have the expected behavior.

4.2 The Three Axes Experiment

In this experiment stage, the patient was free to move the UR3's end-effector to any possible place, respecting the limitation of the robot. Before the training starts, the sensor was again re-calibrated due to the same reasons for the first part. As the algorithm works with a more complex system and should provide the resistance force in the three axes, some modifications need to be made. Therefore, the self-control was built considering the increment of the resistance force separately. The reward was obtained to the entire system, i.e., only one Q-matrix was responsible to capt the information, but the choices to increase or decrease was executed separately considering the values of force on some axes.

The measured resultant force is presented in Figure 11. This force is too large in the first episode, but in the sequence, it seems to normalize nearby an acceptable value.

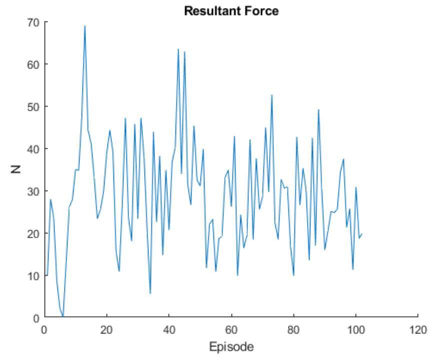


Figure 11: Resultant force measured by the sensor.

The same happens for the robot force. Figure 12 shows this force for the x-axis. The force seems to remain nearby value of 4 N. Similar behavior is noted in the other two axes. It is also important to remember that the learning is linked to the actions of increasing, decreasing or maintaining the force.

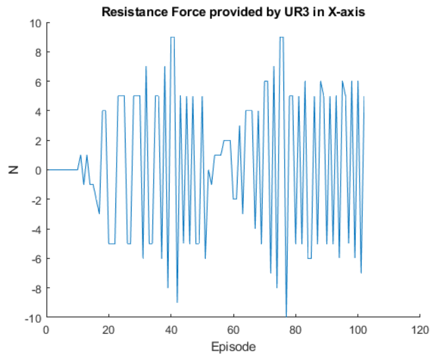


Figure 12: robot force in X-axis.

Even using self-control, the learning was not perfectly suitable for this problem. The algorithm grants the rewards based on the resultant force and this ensures that the system always will search for a value inside of the range specified. However, as only one Q-matrix controls the three axes, the value of an axis interferes with each another. Thus the system did not learn the better force for the motion in each axis, but learn some range of values that can be used in the three axes, independently to seek the desired resultant force.

A solution for this problem is to create an algorithm that is capable to perform a decision based on the robot force on three axes, the actions and the position on three axes. This implies a Q-matrix with ten dimensions. Another solution is to implement three tri-dimensional Q-matrix, each one evaluating each axis and another that will evaluate the movement in terms of the resultant force.

5 CONCLUSIONS

The rehabilitation is actually of main importance for the society. The use of a collaborative robot to perform this task could be a tool to help the therapist to treat his patients. This paper addressed a UR3 collaborative robot as an assistant to the rehabilitation process. The main contribution of this work is the development of a system that brings together emerging technologies to improve the human-robot relationship. Besides, the insertion of a self control module removes the need for the robot's path planning and its configuration to each patient. Since there is a simulation environment for the proposed system, it possible to identify any failure and make adjustments, principally when this technology is applied together to human touch. The reinforcement learning was used to adjust parameters and adapt the movements to the patient on-the-fly. Once the simulation is tuned, the UR3 robot is used to test the SARSA algorithm in a real environment. It allows validating the proposed system. As future work, more data can be acquired from the patient to adapt the robot movements more truly.

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