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Simulation of interactive motor behaviours in game theory framework for upper-limb rehabilitation

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ABSTRACT

An increasing number of individuals are affected by neurological diseases worldwide. Nowadays, stroke is the leading cause of adult disability in western countries, with upper limb hemiparesis being one of the most common consequences. Therefore, there is a growing interest in developing robotic interfaces to provide neurologically affected individuals the right amount of assistance to guarantee a great recovery. The interactive control of such rehabilitation robots with a stroke survivor is critical to motor recovery, and a successful rehabilitation requires the patient to be engaged in motor task execution.

This thesis focuses on the new development of an interactive robot controller, and aims to ensure that differential game theory can be used as a framework to describe various interactive behaviours between a robot and a human user. In this thesis, it will be simulated the interaction between a robot and an injured human user who is recovering after stroke in the game theory framework, demonstrating that it can induce a stable interaction between the two partners by identifying each other's control law and allow them to successfully perform the task with minimum effort.

In this thesis is expected to find a detailed description of the different interactive motor behaviours that exist between a rehabilitation robot and a human user: collaboration, cooperation, competition and co-activity. It will also contain the simulation of these behaviours. In the description of the human-robot interactive motor behaviours, it will be seen that some of these behaviours are modelled in the simulation in the game theory framework, such as collaboration, cooperation and competition, while co-activity consists on a problem where the robot and the human are modelled as two independent linear quadratic regulators.

Finally, it will be provided a comparison between the use of a game theory controller and the use of a linear quadratic regulator controller for the development of a rehabilitation robot and it will be demonstrated why a game theory controller is a better option for robots that work in physical contact with humans.

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1. INTRODUCTION

The use of robotic systems working in physical contact with humans has increased during the last decades [1]. Unlike traditional robotic manipulators used in industries where they have little contact with human operators, there must be trust in the safety of the robotic system working with humans such as rehabilitation robots, as patients depend on a reliable relationship with the robot. Nowadays, rehabilitation robotics have made little use of the opportunities of interactive control [1]. Typical rehabilitation robots are either fully controlled by the operator or their control law does not adapt during the interaction with the human user [1]. It is necessary for a rehabilitation robot to react and adapt to a specific motion behaviour according to a desired control strategy.

The number of patients requiring physical rehabilitation for hemiplegia as an effect of stroke is increasing year after year. Rehabilitation robots are an adequate platform for recovery of the brain motor function in patients with neurological injuries, as they can offer repetitive therapy and can measure precisely the patient's improvement [2]. This thesis aims to deepen in a new research that shows that using a differential game theory controller in rehabilitation robots is definitely useful for versatile physical human-robot interaction [1]. This theory yields insight into how robots can understand human's actions through physical interaction and how they can adapt their behaviour to help humans reaching their goals.

1.1. CONTEXT

This chapter introduces the context of the thesis and presents a few concepts that are required to be mentioned to work in this domain.

This thesis is based on the paper "Differential game theory for versatile physical human-robot interaction" [1], done by researchers of the *Imperial College of Science*, the *University of Sussex* and the *Nanyang Technological University*. The aim of the paper is to develop an interactive robot controller able to understand the control strategy of the human user and react optimally to their movements [1]. In this thesis, it will be simulated the human-robot interaction for the upper-limb rehabilitation and will be tested the new discoveries made in this field of study.

In post-stroke rehabilitation therapy with rehabilitation robots, there is an interaction between the robot and the patient, and it is crucial that they interact in an effective and optimal way to promote patient's recovery [3]. The findings done by the researchers in [1] are important findings in the field of rehabilitation robotics because by understanding human's actions, robots can react optimally to them and adapt the assistance that it is necessary for the patient to recover progressively.

Firstly, some concepts about the brain's ability to recover and stroke will be introduced, to deepen in the subject that aims this study. Subsequently, some aspects of rehabilitation robotics will be introduced, and the context description will be finished with the explanation of game theory and adaptive control, the two main principles that are applied to simulate a versatile human-robot interaction.

1.1.1. Neuroplasticity

Neuroplasticity or brain plasticity is a term that refers to the brain's ability to change and adapt as a result of experience and behaviour [4]. *Neuro* refers to neurons, the nerve cells that are the building blocks of the brain and the nervous system, and *plasticity* refers to the brain's malleability. In terms of stroke recovery, it refers to the ability of the brain to rewire or reorganize itself after an injury [5].

Until the middle of the last century, psychologists and researchers thought that changes in the brain's structure could only have place during childhood, and it was thought that during adulthood the brain's structures were unalterable. However, recent investigations demonstrate that the brain continues on creating new neurological connections and changing the existing ones with the purpose to adapt to new experiences, learning from the behaviour and the new information to create new memories [5].

Neuroplasticity allows neurons to regenerate both anatomically and functionally and form new synaptic connections[1]. This adaptive potential of the nervous system allows the brain to recover from disorders or injuries and can reduce the effects of structural alterations produced by different pathologies [6].

[1] Connection where the information from one neuron flows to another neuron.

Brain alterations in genetic or synaptic levels are both caused by experience and by a variety of environmental factors [6]. New knowledge acquirement occurs in many ways, for many reasons and at any time throughout life. Children acquire new knowledge in large quantities, producing significant brain changes in those moments of intensive learning. New learning can also derive from the presence of neurological damage that has occurred, for example, through a stroke, when the functions supported by a damaged brain area deteriorate, and they must be learned again.

Nowadays it is understood that the brain possesses the remarkable capacity to reorganize pathways, create new connections and even create new neurons, a phenomenon called neurogenesis. These new neurons require support from neighbouring cells, blood supply and connection with other neurons to survive [6].

Characteristics of neuroplasticity

The main characteristics of neuroplasticity are the following ones [5]:

- *i.* It can vary with age. The brain tends to change a lot during the early years of life: young brains tend to be more sensitive and responsive to experiences than older brains.
- *ii.* Plasticity is ongoing throughout life and involves brain cells other than neurons.
- *iii.* Brain plasticity can occur for two different reasons. It can occur as a result of experience, learning and memory formation, or as a result of damage to the brain. When it occurs due to brain damage, e.g. as during a stroke, the brain's areas associated with certain functions may be damaged. Eventually, healthy parts of the brain may take over those functions and the abilities can be restored.
- *iv.* Genetics plays an important role in brain plasticity.
- *v.* Brain plasticity is not always an improvement. The brain can be influenced by pathological conditions that lead to detrimental effects on the brain and behaviour.

There are two types of neuroplasticity [7]:

- *i.* *Structural neuroplasticity*: Refers to changes in the strength between synapses.
- *ii.* *Functional neuroplasticity*: Depends upon two basic processes; learning and memory. It can cause permanent changes in synaptic effectiveness.

The best way to encourage neuroplasticity after a stroke is with massed practice. It can be done with two methods: task repetition and task-specific practice. Research is still needed in the area of brain plasticity and stroke rehabilitation: it is demonstrated that brain reorganization is possible, but there are only limited rehab treatments that address neuroplasticity [8].

Some examples of how neuroplasticity can heal the after-effects of stroke are the following ones [6]:

i. Memory impairments can be improved with practice of memory games.
ii. Mobility impairments can be improved with practice of rehab exercises.
iii. Speech impairments can be improved with practice of speech therapy exercises.

1.1.2. Stroke

A stroke is a cerebrovascular disease that occurs when the supply of blood to the brain is either interrupted or reduced. If the interruption lasts more than a few seconds, the brain does not get enough oxygen or nutrients, which causes brain cells to die within minutes, and it can cause lasting brain damage, long-term disability or even death [9]. A stroke is characterized by its sudden occurrence and represents the second cause of death and the first cause of disability in western countries [10]. According to the *World Health Organization* [11], stroke was the cause of almost 6 million deaths worldwide in 2016. This disease has remained as one of the leader causes of death in the past 15 years, and although it has a higher incidence in people over 60 years, in recent years the incidence of stroke in young people has been increasing.

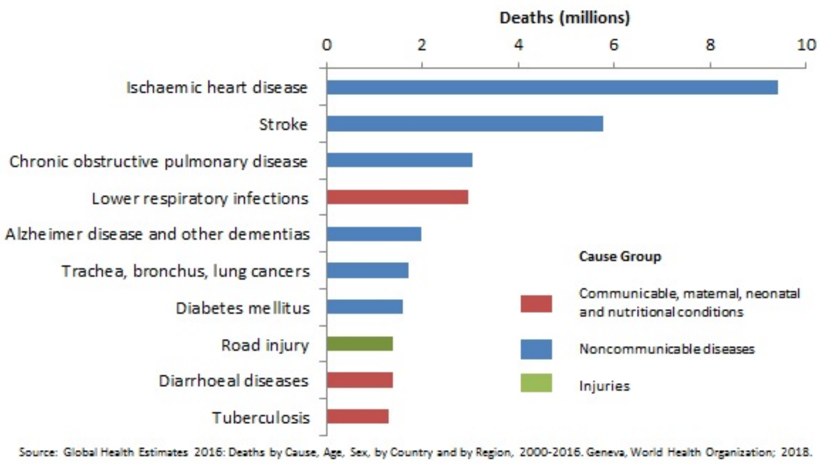

Figure 1.1. Top 10 causes of death, 2016. Image from [49].

Stroke is the leading cause of adult disability, with upper limb hemiparesis[2] being one of the most common consequences [4]. Regaining voluntary arm movement is one of the major goals of rehabilitation [12]. Hence, there is an increasing interest in incorporating the latest advances in neuroscience, medicine and engineering to improve the efficacy of conventional therapies.

Types and causes

Stroke can be classified into two different types depending on its cause [13]:

i. *Ischemic stroke*: This type of stroke is the most frequent (up to 85% of the total [14]) and is caused by a significant decrease of blood flow to a part of the brain. This decrease of blood flow is caused because a brain blood vessel is blocked by a blood clot. If this clot, called thrombus, blocks an artery to the brain and stops blood flow, the stroke is called a *thrombotic stroke*. In contrast, if the clot travels from its original site and blocks an artery downstream, the stroke is called an *embolic stroke*. How the brain is damaged or affected depends on exactly how far downstream in the artery the blockage occurs.

In most cases, the carotid or vertebral arteries are not completely blocked and a small stream of blood goes to the brain. The reduced blood flow to the brain causes the cells to starve of nutrients and oxygen. During a stroke, there is a core area where blood is almost completely cut off and the cells die within a few minutes. However, there is a larger area known as the ischemic penumbra that surrounds the core of dead cells, and it consists of cells that are impaired and cannot function, but are still alive.

This type of stroke is treated by removing the obstruction and restoring blood flow to the brain.

ii. *Haemorrhagic stroke*: This type occurs when a blood vessel becomes weak and bursts open causing a blood leakage into the brain. Although this type is less frequent than ischemic strokes (it is only between 10 and 15% of the cases [15]), mortality in haemorrhagic strokes is considerably higher. However, long term recovery for stroke survivors is usually better.

[2] Reduced muscle power or tone on one side of the body.

It can be caused by hypertension, a vascular malformation or as a complication of anticoagulation medications.

This type of stroke usually requires surgery to relieve intracranial pressure caused by bleeding.

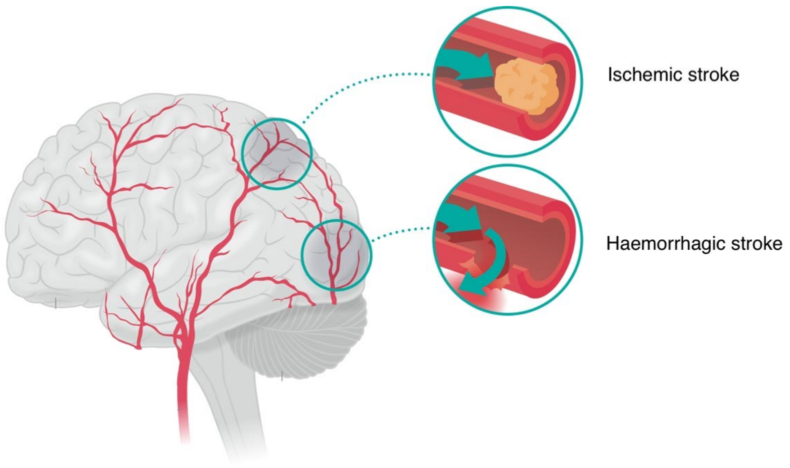

Figure 1.2. Stroke types. Image adapted from [50].

Regardless of which type of stroke has been suffered, it is critical that victims receive emergency medical treatment as soon as possible for the best possible outcome to be realized.

Consequences

The consequences derived from a stroke will depend on the location of the lesion and its extension. The most common impairments are [16]:

i. *Motor impairments*: This type of impairment has the highest prevalence, affecting about 80% of the stroke survivors [17]. It includes hemiparesis, spasticity[3], reduced coordination, reduced joint stability and joint mobility, balance impairment and an altered gait pattern.

[3] Condition in which certain muscles are continuously contracted and causes stiffness or tightness of the muscles.

ii. *Cognitive disorders*: This includes cognitive decline, altered consciousness, attention or alertness, reduced energy and motivation and changes in temperament.
iii. *Sensitive disorders*: Altered proprioception.
iv. *Language disorders*: Disorders such as dysphonia[4], dysarthria[5] and dysphasia[6].
v. *Visual impairments*: Loss of visual acuity.
vi. *Perceptual disorders*: Agnosia[7], apraxia[8] and neglect.

As scientific studies show [18], it seems that in any of the above cases, the earlier an appropriate neurorehabilitation treatment is initiated by an expert multidisciplinary team, the better the long-term functional results will be.

Risk factors

There are certain factors that can raise the risk of a stroke. The primary risk factor for a stroke is having high blood pressure, but there are other major risk factors, such as diabetes, having heart diseases that can cause blood clots that lead to stroke, smoking, a personal or family history of stroke, age (the risk of stroke increases as one gets older), gender (men are at higher risk) and race. There are also other factors that are linked to a higher risk of stroke, such as not getting enough physical activity, high cholesterol, unhealthy diet or having obesity.

Some of the risk factors, such as the age, the gender, heredity or the race of the patient cannot be modified, but many of them can be changed, treated or controlled, such as high blood pressure, diabetes, heart diseases, high cholesterol, smoking, poor diet, lack of physical activity and obesity.

The time between the brain attack and the admission to the hospital can also be considered as a risk factor. If the patient is quickly admitted to the hospital, medicines or surgeries may minimize or eliminate post-stroke disabilities [19].

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[4] Dysfunction of the voice.

[5] Motor speech disorder characterized by poor articulation of phonemes.

[6] Full or partial loss of verbal communication skills.

[7] Inability to interpret sensations and hence to recognize things.

[8] Inability to perform particular purposive actions.

Recovery

Recovery of body functions and activities involves processes such as restitution, substitution and compensation [20]. The first one means to restore the functionality of damaged neural tissue; substitution refers to the reorganization of partly spared neural pathways to relearn lost functions; and compensation implies the use of biological structures or functions different from the ones originally used before the injury, e.g., using a non-paretic limb to execute a task that had been executed with the limb before the injury. Approximately 60% of the patients with a first stroke will regain their basic activities of daily living, 80% will regain independence in walking and only 40% to 50% will regain some upper limb function [20], so it is really important to focus on upper-limb rehabilitation to try to increase the percentage of upper-limb mobility regaining.

Some studies with repeated measurements have demonstrated that almost all stroke survivors show at least some neurological and functional recovery in the first three to six months [20]. While patients recover basic skills during the first six months after stroke, they attend rehabilitation to relearn progressively more complex and demanding tasks. Beginning to reacquire the ability to carry out basic activities of daily living represents the first stage in a stroke survivor's return to independence. For some stroke survivors, rehabilitation will be an ongoing process to maintain and refine skills and could involve working with specialists for months or years after the stroke.

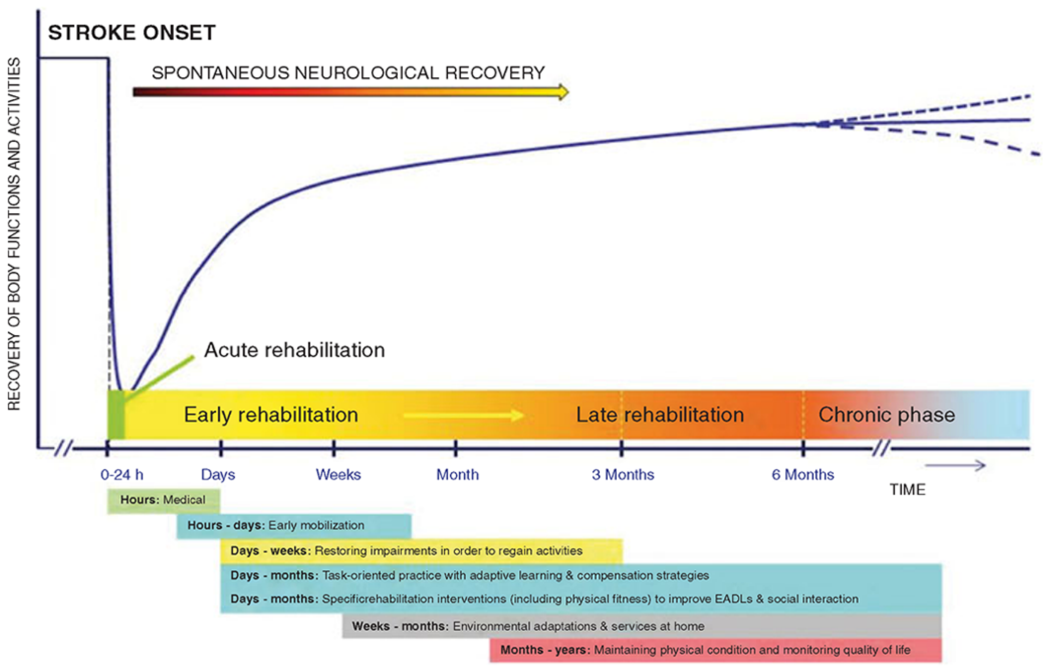

Figure 1.3. Hypothetical pattern of recovery after stroke. Image from [51].

Rehabilitation is necessary to bring the recovery at a higher level. Researchers work on computational neurorehabilitation models to get a better understanding of the neurorehabilitation process and to increase the predictions of improvement. Approximately 75% of stroke survivors will be dependent for a number of daily life activities, and this is mainly due to a lack of abilities for using their paretic upper limb [21]. The objective of the rehabilitation therapies is to bring the patient to the maximum level of autonomy that he could get in order to reduce the disability. To reach this objective, some recommendations for upper-limb rehabilitation are the following ones [22]:

i. *Task-specific training*: This type of rehabilitation involves practice of tasks relevant to daily life.

ii. *Repetitive task training:* Repetitive task training involves the repeated practice of functional tasks.

iii. *'Hands-on' therapy:* The arm and the hand joints are moved by a therapist, who may provide partial or full assistance.

iv. *Constraint-induced movement therapy (CIMT)*: CIMT involves restricted use of the unaffected limb for several hours a day.

v. *Bilateral arm training*: Involves the execution of identical activities with both arms simultaneously.

vi. *Robotic therapy*: Robotic devices are devices that can move passive limbs, while providing assistance or resistance. They may be used to deliver repetitive task training or task-specific training.

1.1.3. Rehabilitation robotics

The interaction between robots and humans has experienced great growth in the last years. Rehabilitation therapy based on robots has become a topic of interest for many rehabilitation therapists [23]. Robotic rehabilitation is addressed to provide assistance to individuals with severe neurological disorders such as stroke and rehabilitation robots are intended to function in a human-centred environment with the necessary interaction of the patient [3]. Rehabilitation robots are machines or tools that are specifically designed to provide a diagnostic (measurement and assessment) or therapeutic benefit improvement of the function. Their main goal is to train and enhance the patient capabilities affected by neuro-muscular deterioration such as stroke.

The global objective of any researcher focused on developing a rehabilitation robot, either for upper or lower limb, is to adhere to the paradigm *assistance-as-needed* [21]. This type of assistance consists of remaining as low as possible in order to prevent slaking behaviour from the patient to occur, but also giving enough aid to reach the goals of the rehabilitation. The concept of assistance varies depending on the human involved and their dynamics. An efficient assist-as-needed control strategy can be achieved by understanding the human dynamics involved, developing efficient hardware and an interactive control approach [21].

Robotic neurorehabilitation is attractive because of its applicability across a wide range of motor impairments, its ability to offer high intensity and a goal-directed training and its high measurement reliability [24]. This type of therapeutic assistance can also be extended to patients with muscle disorders or with other post-operative rehabilitation requirements. Studies on the effectiveness of robotic neurorehabilitation have proven that robots are beneficial in measuring the patient's impairment level [24].

Conventional neurorehabilitation seems to have little impact on impairment [25]. Robotic neurorehabilitation has the potential for a greater impact on impairment due to its easy deployment, its applicability across of a wide range of motor impairment, its high measurement reliability and its capacity to deliver high dosage and high-intensity training protocols.

<u>Types of rehabilitation robots for the upper-limb</u>

Generally, there are two classes of upper-limb rehabilitation robots: <u>end-effector</u> robots and <u>exoskeletons</u> [21]. The first ones are the ones that will be taken into account when making this study. End-effector devices work by applying forces to the final segments of limbs [26]. They are easy to install and require only a few adjustments before the start of the therapy. In the second type of robots, every joint of the arm is actuated by a multi-body actuated structure. Exoskeletons allow to deliver individual assistance to each joint but they have a larger and more difficult installation.

Figure 1.4. End-effector rehabilitation robot. Image from [52].

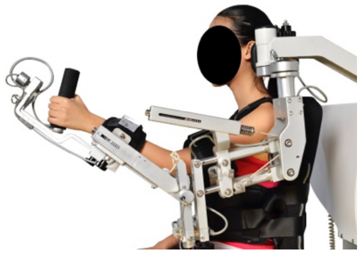

Figure 1.5. Exoskeleton rehabilitation robot. Image from [53]

1.1.4. Game theory

Game theory is a branch of applied mathematics and economics that studies situations where players choose different actions in an attempt to maximize their returns [27]. Although it has been recently used in artificial intelligence and cybernetics, game theory is usually used to understand how economic agents decide and interact with each other in order to maximise their own gain. Nowadays, game theory application concern a broad range of behavioural relations, and is a general term for the science of decision making in humans, animals and robots.

Game theory describes and analyses situations where interactive decisions take place, and it appears as a framework to study human-robot motor interaction [28]. It comprises a set of analytical tools to predict the response of interactions between decision makers. In game theory, multiple agents interact in a game, competing or collaborating to reach a goal, and the term agent refers to the part involved in the performance of a task [29]. Interactions between agents are represented by the influence each agent has on the result through a cost function representing its objectives. Each agent has its own strategy and will try to optimize its performance, knowing that every other agent will play optimally. The job of finding an optimal strategy in differential games is related to optimal control[9] [28].

Interaction between the human and the robot is represented by the influence that each agent has on the resulting outcome through a cost function representing its objectives, as it was mentioned

[9] The process of finding the control and state law for a dynamic system over a period of time so that the performance of system is optimal with respect to some criterion.

before. Game theory has been shown to be suitable for analysing the performance of multiagent systems [28], in which human-robot interaction is considered a two-agent system. Given a game with known objectives (modelled as cost functions) for linear systems, a method that solves a coupled Riccati equation can be used to obtain the optimal control [29].

The stable state conditions in which each agent is assumed to know the equilibrium strategy of the other agent and no agent has anything to gain by changing only his own strategy unilaterally, is known as Nash equilibrium [28]. From the definition of the Nash equilibrium, it is understood that each agent considers its own cost function and its performance cannot be improved by changing the control strategy unilaterally [29].

Game theory algorithm follows iterative computing. At each iteration, each agent computes a strategy on how to reach the task, selects the best action according to its strategy and checks if the coordination is successfully established with the partner. If the coordination is successfully established, the learning algorithm ends; if not, a new iteration starts at the first step and each agent updates their strategy [30].

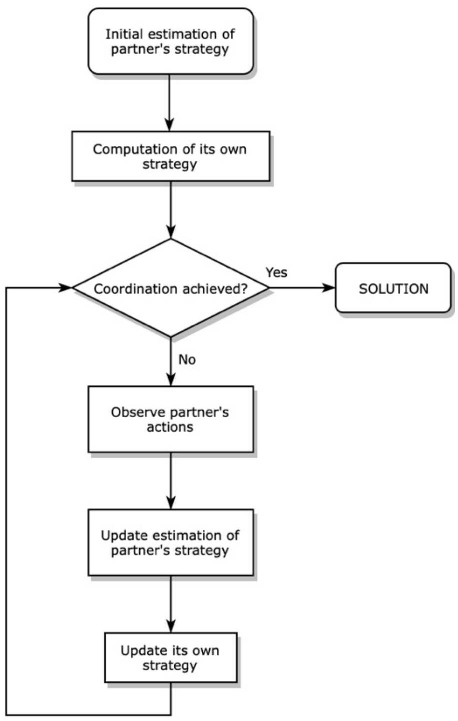

Figure 1.6. Game theory algorithm. Image adapted from [29].

By using a game theory framework, it is used a group of cost functions to organize, understand and reproduce human motor behaviours of interactions with partners. As soon as the task has been characterized, the utility function of each partner is chosen based on the assumption that both agents will work towards the objective of the task [30].

Although game theory typically assumes knowledge of the partner's dynamics and control strategies and a contact robot is not able to know the sensorimotor control of humans, it is suggested that differential game theory can be used as a framework to describe interaction behaviours between the robot and the human [1]. Interaction benefits occur with the capability of the other agent to understand the partner's sensorimotor control to adapt one's own control.

1.1.5. Adaptive control

The main issue with trajectory tracking and impedance control based training is that the controller parameters cannot be varied based on real-time judgement of the patient's abilities. Adaptive assistance is used to enhance the patient's active participation in the training process. The term adaptation is used for real-time tuning of controllers designed for robotic actuators to match patient's disability level and to actively involve him in the training process [31].

Adaptive control is able to handle with the disturbances by acting directly on the controlled variables and the disturbance affecting the controller's performance. Adaptive approaches have also been used to adjust the desired trajectory. An adaptive control system automatically compensates for variations in system dynamics by adjusting the controller characteristics so that the system performance remains the same, so the adaptive control system includes elements to measure or estimate the process dynamics and other elements to change the controller characteristics so the overall system performance can be maintained [32]. The essential steps of the adaptive system are the identification of system dynamics, the decision and the modification. Once the system is identified, the decision function operates and this activates the modification function to modify the parameters and to maintain the optimum performance [33].

To sum up, an adaptive control system can be defined as a feedback control system able to adjust its characteristics in a changing environment so that some specified criteria are satisfied [32].

The general architecture of an adaptive control system contains four basic components [34]:

i. The system that has to be controlled. It involves unknown parameters.
ii. A reference model for the determination of the desired system output.
iii. A feedback controller with adaptive parameters.
iv. An adaptation mechanism for updating the controller parameters.

It is assumed that the structure of the controlled system is known, and only its parameters are unknown [34]. The reference model provides the ideal response of the system that must be achieved through the adaptation of the parameters, and the control law must have the ability to follow perfectly the reference response. This means that when the system parameters are exactly known, the controller parameters should make the system output identical with the output of the reference model.

1.2. STATEMENT OF THE PROBLEM

In the study done in [1], a game theory controller is developed. It is supposed to be an interactive robot controller able to understand the control strategy of the human and react optimally to their movements. The intention of developing this is to demonstrate that it can be induced a stable interaction between two partners by identifying each other's control law and the task can be executed with the minimum effort for the trainee [1].

This thesis will be focused on the simulation of the interaction between a human and a robot, but not on implementing the controller in a real robot. It has been used adaptive control and Nash equilibrium game theory to simulate the human-robot interaction [1], where the robot and the human can understand each other's behaviour in order to better anticipate their movements and respond to them. In the work done by the researchers, it has been used for the first time game theory to enable rehabilitation robots to assist humans in a safe and versatile manner [1].

Interactive control of rehabilitation robots with the patient is necessary to motor recovery [3], as clinical tests [35] have evidenced that passive training is not as much efficient as maintaining the patient actively engaged in the task execution.

The properties that efficient robot-assisted neurorehabilitation should have are [3]:

i. The interactive control must be safe.

ii. It must not interrupt the natural movements of the patient, so it should be smooth.

iii. The control should not constrain the limb movements, just guide them.

iv. It should consider the current movement of the patient and must be able to react to it appropriately.

v. The control should be adapted to the motor capabilities of the patient.

In order to have an interactive control framework that fulfils all the previous properties, the physical interaction with the patient should be regulated by a robot as if it was therapy with a human physiotherapist [3].

Having a more advanced sharing between humans and robots would benefit the neurorehabilitation scenario, in which robotic devices assist patients to develop their movement abilities, as humans would have a more specific rehabilitation, and therefore a greater recovery. It is needed to have task sharing beyond master-slave roles, as for example in tuning motion assistance correspondingly in order to help post-stroke patients actively working on improving their abilities. The robot has to be able to provide assistance as needed and also challenge humans, such as providing less assistance than needed, a type of assistance that can keep humans engaged and prevent them from desisting. In the case that the robot assists the human less than he or she needs, the robot pushes the human to increase his or her effort in order to complete the task [36].

In this thesis, robot and human cost functions are modelled in a game theory framework to specify the task objectives, and therefore the desired control strategy. Understanding how humans interact in tasks is critically important in designing robots interacting with humans [28]. This may help to create robots that interact with humans as humans do. The partner's motor behaviour and the adaptation are obtained by the use of mathematical tools from game theory, optimal control and adaptive control. Then, it is assumed that the patient and the robot could be modelled as two agents with a task and a behaviour specified by a quadratic cost function to be minimized [28]. Neuroscience studies [37] have demonstrated that this cost function to be minimized is the weighted sum of kinematic error and effort.

As the human and the robot are coupled through physical contact, they can deviate each other from its desired motion unintentionally [36]. The major innovation is using game theory to determine how the robot responds to the effects of the interaction with a human. In a typical physical interaction between a human and a robot, robots either control the human to reduce error, which could harm the human, or they allow the human to move the robot easily, which increases the error in the task [36]. With a game theory controller, the robot uses the difference between the expected and the actual motions to estimate the human's strategy, and by knowing this strategy, the robot can change its own strategy to adapt to human needs, i.e. the robot can increase its effort if the human is not able to complete the task or can decrease the help it gives to the human if he or she is able to perform the task easily.

With the use of game theory for the human-robot interaction, it can be determined the Nash equilibrium, which indicates that both agents have the best response to its partner while also considering their own cost function.

To sum up, the interactive game theory control enables the robot to:

i. Estimate the patient's controller during interaction.
ii. Adapt to the partner in order to ensure a desired interactive behaviour.

Could it be considered that a game theory controller is better for rehabilitation robots than an LQR controller? The Linear Quadratic Regulator (LQR) is a method that provides optimally controlled feedback gains to enable the closed-loop stable and high performance design of systems [38]. The LQR optimization objectives are frequently employed due to their tractability, their viability of implementation and their broad applicability of the quadratic utility function [39]. The main differences between both of them is that the game theory controller is a priori able to estimate its partner's behaviour, while the LQR controlled is not. Knowing this, it is usual to think that the game theory controller will provide a more accurate rehabilitation, as it can adapt to what the human needs by knowing its control strategy. In the thesis will be compared both controllers and will be seen whether the initial beliefs are the correct ones.

1.3. OBJECTIVES

As it is showed before in the introduction, recent studies established that the game-theoretic framework represents a significant advance in physical human-robot interaction, as it allows the robot to change among some different behaviours by estimating a human's strategy during the movement.

The main objectives of this thesis are the following:

i. Improve the understanding on how stroke patients can have better rehabilitation of the upper extremities taking into account this new discovery in the field of rehabilitation robots by analysing the research done previously by the researchers of the *Imperial College of Science*, the *University of Sussex* and the *Nanyang Technological University*.

ii. Understand and compare the different types of interaction behaviours that exist between a robot and its human user and simulate them, analysing if the results are the expected ones.

iii. Discuss if a game theory controller is better than an LQR controller in a rehabilitation scenario.

The thesis is articulated around these objectives. Each one of them is explained in the following chapters and all the study done in this thesis is based on the publication "Differential game theory for versatile physical human-robot interaction" done by the researchers of the *Imperial College of Science*, the *University of Sussex* and the *Nanyang Technological University*.

2. METHODS

The aim of this chapter is to develop the methods that are employed in the thesis. It pretends to provide a detailed explanation of the theoretical notions and how these notions are implemented in the simulation framework to obtain the results that can corroborate that implementing a game theory controller is a good option for reaching a good interaction between a rehabilitation robot and a human.

2.1. CLASSIFICATION OF INTERACTIVE MOTOR BEHAVIOURS

Robots can improve rehabilitation by increasing the intensity of training and allowing patients to practice motor tasks in a more repetitive way. Many previous studies [40] have examined physical interactions between humans and robots to try to determine how robots should be controlled to train, collaborate with or assist humans.

The aim of this thesis is to simulate a controller able to interact with the human user in all the possible ways of robot-human interaction, i.e. simulating all the possible behaviours. Because of that, it is important to understand the different ways a robot and a human can interact for implementing a controller that can work in all these possible behaviours.

First of all, it can be differentiated two types of tasks: <u>divisible tasks</u> and <u>interactive tasks</u>. The first group involve the tasks that can be done by each agent independently and in which both agents do not need to know anything about their partner to succeed in their subtask. In this type of tasks, each agent minimizes its own error and cost function. The type of behaviour that includes divisible tasks is called <u>co-activity</u>. The second group of tasks, the interactive tasks, are those in which the activity of each agent affects the other agent. In this type of tasks, it can be identified three types of behaviours: <u>cooperation</u>, <u>collaboration</u> and <u>competition</u>. Cooperating agents work towards the same goal and they need each other to complete the task, but they do not have the same behaviour. In collaboration, there is not a role distribution at the beginning and they try to develop an accordant solution to reach the goal. In competition, both agents focus only on their own action and effort and try to interfere in the other's performance [28]. All these behaviours will be described down below.

Another way to classify the tasks is through agonistic and antagonistic tasks. In antagonistic tasks, one agents is detrimental to its partner due to conflicting interests. This is why competitive behaviours are considered antagonistic tasks. In general, in antagonistic tasks each agent have distinct goals [28]. In agonistic tasks, the improvement of one agent contributes to the improvement of the total task, so this type of task corresponds to cooperation and collaboration types of behaviours.

The next scheme is used to classify the different human-robot interaction behaviours found in the literature [28].

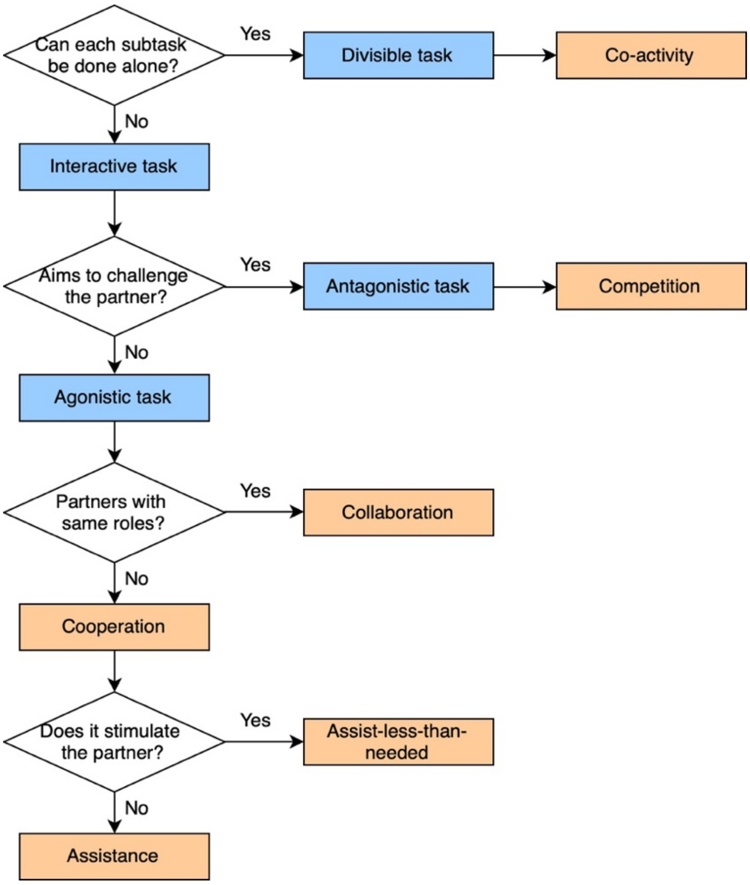

Figure 2.1. Determination of motor interaction behaviour. Blue rectangles are tasks and orange rectangles are interaction behaviours. Image adapted from [24].

The behaviours that perform interactive tasks can be classified in three categories, as it is said before: cooperation, collaboration and competition. Competition is observed during antagonistic tasks as a non-cooperative game[10], and cooperation and collaboration are observed during agonistic tasks as a cooperative game[11]. These behaviours will be described down below.

2.1.1. Collaboration

Collaboration refers to the act of one agent working together with another agent, combining their strengths to accomplish a goal [41]. Thus, collaboration involves the mutual engagement of agents in a coordinated effort to solve the problem together [42]. In this case, no agent has the incentive to reach the solution alone. It is modelled as a symmetric behaviour, i.e. there is an equal distribution of responsibilities between both agents, with a positive influence on the partner. In collaboration, each agent tries to minimize its own error and effort and the partner's error and effort. In collaborative behaviour there is no initial role distribution; the role distribution is done spontaneously based on the interaction history.

2.1.2. Cooperation

Cooperation considers the division of a task among the agents, where each participant is responsible for a part of the problem solving [42]. In this case, there is a role assignment at the beginning of a task, and the roles are maintained through the execution of the task. Thus, cooperation is modelled as an asymmetric behaviour.

The role assignment can be implemented in the simulation through a sharing rule that specifies that the sum of the robot's cost function weight and the human's cost function weight should be equal to some total weight (C), so both agents share the effort done to reach the task (explained in *section 2.2.*). Then, the main difference between cooperation and collaboration is that the first one fixes the task performance through a total weight (C) and both agents share the effort done to reach the goal.

---

[10] Game with competition between individual agents.

[11] Game with coalitions between agents.

There are two special cases of cooperation. The first one is assistance, which comes up when C is set to let the robot fulfil the task alone, so the robot will gradually take over the task while the patient becomes passive (as humans tend to relax during motor actions). The other case is assist-less-than-needed, which is designed to keep the human engaged during physical rehabilitation. This case is implemented by setting C to not make the robot reach the target alone, so this will induce the human to increase their effort in order to reach the target [1].

2.1.3. Competition

Competition is principally observed during antagonistic tasks. In this type of behaviour, both agents focus on their own error and effort and even may try to impede the partner's performance. In the case of rehabilitation robots, which cannot harm the human and their goal is to make him or her recover from a disease, the competitive behaviour can be understood as a cooperative behaviour between the two agents, but with the robot providing resistance instead of assistance, i.e. trying to keep the human away from reaching the task. The resistance in the robot can be modelled with negative weight, so the patients have to increase their effort in order to overcome the negative weight of the robot and fulfil the task.

Cooperation is a type of interaction that may promote motor recovery in neurologically impaired humans, where the robot challenges the trainee. This type of interaction strategy may motivate patients to maximally engage in the physical task. In competition, the robot favour its own goal and minimizes its own effort while maximizing the human's effort and tries to prevent him or her from reaching the target position [3].

Both collaboration and competition involve symmetric behaviours, but their main difference is that collaboration represents helpful interaction while competition represents harmful interaction; this difference is comprised only by a sign change in the cost function weight.

In the next page is presented a scheme of the three interactive behaviours. These are the behaviours that will be modelled in the game theory framework, as each agent needs to know the behaviour of their partner in order to adapt to it

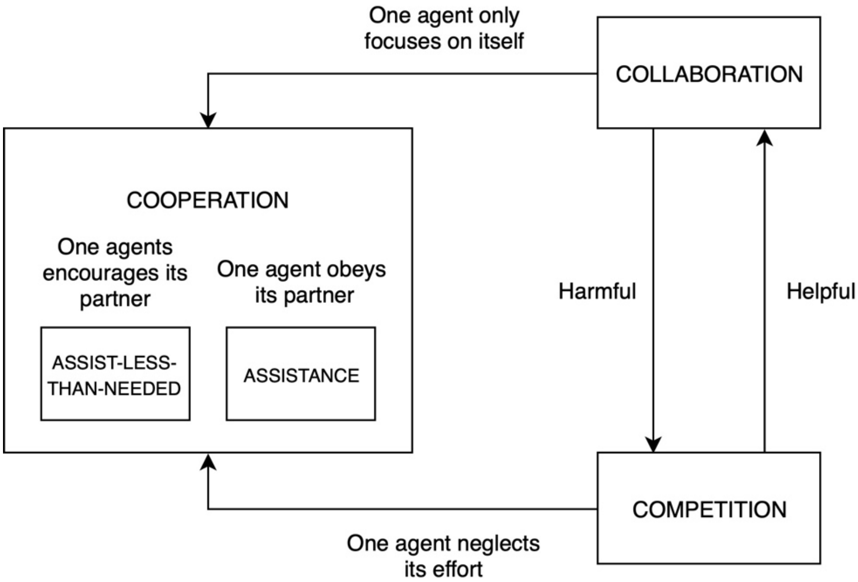

Figure 2.2. Relations between interactive behaviours. Image adapted from [28].

2.1.4. Co-activity

This type of behaviour is the only one that is not modelled in the game theory framework, as in this type of motor behaviour, the human and the robot do not need to know what each other is doing. Although the agents do not estimate their partner's behaviour, they also interact and succeed in the common task. This can be modelled as a problem with two independent LQR instead of a game theory controller.

This type of motor behaviour where the robot and the human perform each task on its own without knowing what their partner is doing, is in many cases an efficient way to perform joint actions, as no sensory exchange is needed, so this enables a safe and simple solution without interference [28].

2.2. SIMULATION

In this section, the algorithm used for implementing the simulation of human-robot interaction in a neurorehabilitation scenario will be described in order to develop the interaction behaviours described in the previous section. The simulation is focused on point-to-point arm movements in Cartesian space, as it is the most popular protocol for upper-limb physical neurorehabilitation [3]. The aim is to analyse how a rehabilitation robot can assist a neurologically impaired human to train arm reaching from a start position to a target position.

The evolution of the agents' state variables is governed by differential equations, and the problem of finding an optimal strategy in the differential game theory framework is related to optimal control [28]. Optimal control deals with finding a certain optimality criterion to be achieved [43]. The use of optimal control also allows for formal and rigorous analysis of conditions that guarantee stability, which is essential to the safety of the interaction between humans and robots. Optimal control is about operating a dynamic system[12] and trying to minimize its cost. When the dynamics are expressed as linear differential equations and the cost function is described as a quadratic function, is a linear quadratic (LQ) problem. The way of resolving this problem is by using a feedback controller like a linear quadratic regulator (LQR). Linear quadratic regulator is a technique based on state feedback to minimize the cost function. In this case, the equations are the LQR ones, but with the difference that there is a coupling effect between both agents, which transforms it from an LQR controller to a game theory controller. When this coupling effect does not exist, it turns out to be a problem with two independent LQR, which is the case of co-activity behaviour.

Differential game theory is used to create a reactive robot behaviour considering the control behaviour of the human user and adapting to it [3]. In game theory, it is considered the Nash equilibrium, which indicates that both agents best respond to the partner while they are also considering their own cost function.

[12] Time-dependent system.

The variables used throughout the simulation are the following ones[13]:

$x, \dot{x}$	Robot's end effector position and velocity
u, u_h	Robot and human motor commands
$\hat{u}, \hat{u}_h$	Robot and human estimated motor commands
I, D	Robot's inertia and viscosity matrices
x_d	Target position
ξ	System state matrix
ξ_h	Human state matrix
A, B	State and input matrices
Q, Q_h	Robot and human state weights
$\hat{Q}, \hat{Q}_h$	Robot and human estimated state weights
L, L_h	Robot and human feedback gains
$\hat{L}, \hat{L}_h$	Robot and human estimated feedback gains
P, P_h	Robot and human Riccati equation solutions
$\hat{P}, \hat{P}_h$	Robot and human estimated Riccati equation solutions
A_r, A_h	Robot and human state matrices
$\hat{A}_r, \hat{A}_h$	Robot and human estimated state matrices
$\hat{\xi}, \tilde{\xi}$	Estimate of system state and state estimation error
Γ, α	Arbitrary positive definite matrix and a positive scalar
C	Desired task performance matrix

The simulation consists of ten back and forth movements between two desired positions ($-x_d$ and x_d). In the simulations done in this thesis, the target position is set as 10 cm. The robot dynamics are simulated using u and human dynamics are simulated using u_h, both set initially to zero. Both robot and human are not supposed to have any initial knowledge of the partner's control, i.e. initially both $\hat{P}_h$ and $\hat{P}$ are set to zero.

Initially, the robot and human state weights (Q, Q_h) are set. The values of these variables depend on the type of behaviour that is being simulated. In the case of collaboration, both of them are positive semi-definite matrices, as both agents provide positive influence to their partners, and in the case of competition, robot state weight is negative semi-definite, which means that the robot

[13] $(\hat{\cdot})$ denotes estimation.

is providing resistance. The state weights can be described as the strength that is given from the agents to fulfil the task.

The continuous-time linear system is described by:

$$\dot{\xi} = A\xi + B(u + u_h), \qquad \xi = \begin{bmatrix} x - x_d \\ \dot{x} \end{bmatrix}$$

$$A \equiv \begin{bmatrix} 0 & 1 \\ 0 & -I^{-1}D \end{bmatrix}, \qquad B \equiv \begin{bmatrix} 0 \\ I^{-1} \end{bmatrix} \tag{1}$$

In the simulation, it is described a robot with an inertia of 6 kg and a viscosity of -0,2 Nm^{-1}. ξ tracks the position error and the velocity. If the controller operates without taking into account the output or the state, the system is called open loop, but if it operates according to the feedback of information about the outputs, the system is called closed loop [44]. In the case of this study, as the controller takes into account the information of the states, it is a closed loop system.

As it is mentioned in the statement of the problem, recent neuroscience studies [37] have proved evidence that human motor control corresponds to the minimization of effort and error. For simulating the human and the robot, it is used a quadratic function that has to be minimized which contains the error (which is described by the state ξ, as it contains the position error) and effort (which can be described by u, as u is the motor command of the agent but as it will be described later, it is computed from the effort done by the agent):

$$U = \int_{t_0}^{\infty} (\xi^T Q \xi + u^T u)\, dt$$

$$U_h = \int_{t_0}^{\infty} \left(\xi^T Q_h \xi + u_h^T u_h\right) dt \tag{2}$$

The state is a matrix including the position error and the velocity, so the state weights include two components corresponding to the position regulation and the viscosity, respectively. As the study focus in reaching a position, all the simulations are done only with the position regulation component, i.e. the viscosity component it is zero in all the simulations carried out.

In the case of cooperation, the human and the robot take complementary roles and share the effort. This is defined through the sharing rule:

$$Q + Q_h \equiv C \tag{3}$$

This enables the game theory controller to continuously modify the contributions between both partners. The assistance type of cooperation arises when C is set to let the robot fulfil the task alone without interaction with the human user. This can be simulated by letting the robot adapt to the human progress, i.e. at each iteration, Q is computed as $Q = C - Q_h$, assuming that the human will be changing unrestrictedly his or her cost function weight, and in the case the human do not provide any force, the robot can reach the task with the specified C by itself. The other type of cooperation, assist-less-than-needed, is designed to keep the human trainee engaged during rehabilitation. This interaction behaviour is implemented by setting C to make the robot short of reaching the target alone, which will induce the human to increase his or her effort in order to reach the task. This is implemented in the simulation scenario by setting a value of C greater than Q, and simulating the human state weight as $Q_h = C - Q$.

Once the values of the weights of each agent are simulated, the next step is solving the Riccati equation in order to compute the human's and the robot's feedback gains (which are the human's and the robot's efforts) and, therefore, the human's and the robot's motor commands. Differential game theory for linear systems [45] has demonstrated that the control input of the robot u and the control input of the human u_h minimize the cost functions in the sense of Nash equilibrium when P and P_h are computed from the coupled Riccati equations, so the Nash strategies can be determined by solving the coupled algebraic Riccati equations. Since the robot and the human control gains L and L_h are unknown to each other, it is needed to estimate the partners controller with $\hat{L}$ and $\hat{L}_h$. L and L_h are a $1x2$ matrices, in which the first component corresponds to the human's position error gain and the second one to the velocity gain. Riccati equations to find the real values of motor commands are computed with the estimated values of the feedback gains, which initially are set to zero and at each iteration they get closer to the real value of the feedback gains. Note how the robot's and the human's controls depend on each other through $\hat{A}_r$ and $\hat{A}_h$, characterizing like this the coupled optimization.

$$\hat{A}_r^T P + P\hat{A}_r + Q - PBB^T P = 0_{2n}, \qquad \hat{A}_r \equiv A - B\hat{L}_h \tag{4.1}$$

$$L \equiv B^T P \tag{4.2}$$

$$u = -L\xi \tag{4.3}$$

$$\hat{A}_h^T P_h + P_h \hat{A}_h + Q_h - P_h B B^T P_h = 0_{2n}, \qquad \hat{A}_h \equiv A - B\hat{L} \tag{5.1}$$

$$L_h \equiv B^T P_h \tag{5.2}$$

$$u_h = -L_h \xi \tag{5.3}$$

After computing this, it is expressed how the estimation of the motor commands affects the states:

$$\hat{u}_h = -\hat{L}_h \xi \tag{6.1}$$

$$\dot{\hat{\xi}} = A\hat{\xi} + B(u + \hat{u}_h) - \Gamma\tilde{\xi}, \qquad \tilde{\xi} \equiv \hat{\xi} - \xi \tag{6.2}$$

$$\hat{u} = -\hat{L}\xi \tag{7.1}$$

$$\dot{\hat{\xi}}_h = A\hat{\xi}_h + B(\hat{u} + u_h) - \Gamma\tilde{\xi}_h, \qquad \tilde{\xi}_h \equiv \hat{\xi}_h - \xi \tag{7.2}$$

These equations are used as an observer for u_h and u, where Γ is a matrix to make $\Gamma - \mathrm{A}$ positive definite.

$$\hat{P}_h \equiv \alpha\big(\tilde{\xi} - \xi\big)\xi^T \tag{8.1}$$

$$\hat{L}_h \equiv B^T \hat{P}_h \tag{8.2}$$

$$A_h = A - BL \tag{8.3}$$

$$\hat{Q}_h = -(A_h^T \hat{P}_h + \hat{P}_h A_h - \hat{P}_h B B^T \hat{P}_h) \tag{8.4}$$

$$\hat{P} \equiv \alpha\big(\tilde{\xi}_h - \xi\big)\xi^T \tag{9.1}$$

$$\hat{L} \equiv B^T \hat{P} \tag{9.2}$$

$$A_r = A - BL_h \tag{9.3}$$

$$\hat{Q} = -(A_r^T \hat{P} + \hat{P} A_r - \hat{P} B B^T \hat{P}) \tag{9.4}$$

Equations (4), (5), (8) and (9) illustrate how game theory works: both agents update their own controller based on the partner's estimated controller in order to minimize their own cost function. In contrast, LQR solution finds the optimal gains by solving independently, without considering the partner's effect, by setting $\hat{L}$ and $\hat{L}_h$ to zero, which simulates that neither the human nor the robot consider their partner's input. By setting the estimated feedback gains to zero, there is no estimation of the state weights and there is no coupling effect when computing the Riccati equations, so the motor commands are not estimated. When doing this, the problem turns out to be a problem with two independent LQR (co-activity case) instead of a game theory controller.

Finally, the state of the system is updated and so the position and the velocity of the end effector are updated too; the position refers to the first position of the state matrix and the velocity to its second position. The algorithm described for doing the simulation of the robot-human interaction is summarized in *figure 2.2.*

Algorithm

Inputs: Current state ξ, target position x_d, robot's cost function weight Q and human's cost function weight Q_h
Outputs: Robot's control input u, human's control input u_h, $\hat{Q}_h$ and $\hat{Q}$
begin
- Define the target position x_d, the state matrix A, the input matrix B and the robot's cost function weight Q
- Initialize $\hat{Q}$, $\hat{Q}_h, u, u_h, \xi, \hat{\xi}, \hat{\xi}_h, \hat{P}, \hat{P}_h, \hat{L}, \hat{L}_h, x, \dot{x}$
- Set the parameters Γ, α, C (in the case of cooperation) and the time of one trial t_f
- **while $t < t_f$ do**
  - Form the state ξ with the initial values of x and $\dot{x}$
  - Simulate the "real" human state weight Q_h
  - In the case of cooperation, adapt the corresponding cost function weight with $Q + Q_h \equiv C$
  - Solve Riccati equations and compute the robot's control input u and the human's control input u_h
  - Calculate the state estimation errors $\tilde{\xi}, \tilde{\xi}_h$ and the estimated states $\hat{\xi}, \hat{\xi}_h$
  - Update $\hat{P}_h$ and $\hat{P}$ and compute $\hat{L}_h, \hat{u}_h, \hat{L}$ and $\hat{u}$
  - Calculate the estimated human's cost function weight $\hat{Q}_h$ and the estimated robot's cost function weight $\hat{Q}$
  - Update the state ξ with $\dot{\xi} = A\xi + B(u + u_h)$ and compute x and $\dot{x}$

Figure 2.3. Proposed algorithm for implementing the simulation.

Finally, to sum up how the different interactive behaviours can be implemented, *figure 2.3.* shows the main characteristics of the different cases in order to implement them.

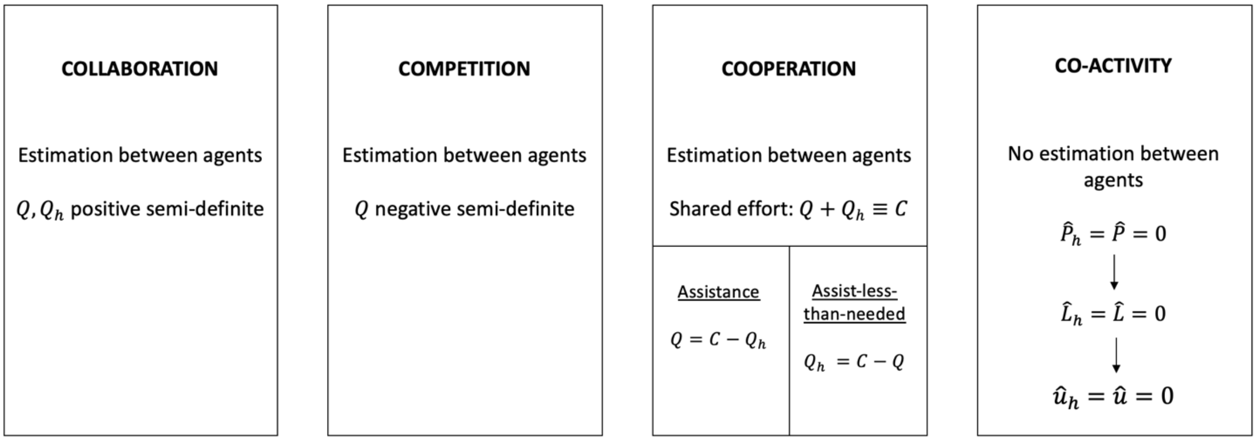

Figure 2.4. Characteristics of the simulation of the different interaction behaviours.

3. RESULTS

In this chapter will be presented the results of the simulations. These simulations intend to demonstrate the properties presented in the previous chapter and exemplify how it can induce the different interaction behaviours. The simulations carried out also aim to examine how the estimation of the partner's controller and the game theory controller induce an adaptive control strategy guaranteeing stability of the interaction and how they can reach the goal successfully. It will be compared the game theory controller with an LQR controller which do not consider the partner's behaviour.

It is shown that the robot can adapt to different situations when the human's strategy changes, either if it changes gradually and slowly (for example when the user is recovering strength), or if it changes drastically (in the case the human is recovering after an injury, when the progress may not be either stable or gradual). For each type of interaction behaviour, it is checked if the task is successfully reached and the effort and the strength that the human has to have so that the task is carried out are measured. Different interaction behaviours are compared and it is proved whether the results are the ones expected after learning about all the interaction behaviours in the previous chapter.

3.1. CO-ACTIVITY vs COLLABORATION

This is the main study done to compare a game theory controller and a LQR controller. As it has been mentioned in the previous chapter, collaboration involves a game theory controller where the robot and the human work together to reach the target position, and the two agents have a positive influence on the partner. The two agents described as two independent LQR controllers arise with the co-activity case, as both agents do not estimate the behaviour of their partner. To study the differences between the collaborative case and the two independent LQR case, the human gains have been compared with different values of human state weight Q_h, i.e. the strength that the human has, and maintaining the robot state weight Q. It is seen in *figure 3.1.* that in all the cases of different human weights, LQR human gains are always bigger than game theory gains. This is because in the co-activity case, each agent do not estimate its partner's control, and so human has to put more effort to reach the task (so the human gains are bigger), and with a game theory controller, the human can reduce its effort, as the controller considers the interaction with the human. As long as Q_h increases, the difference between LQR and game theory gains minimizes, as the robot's influence decreases. The next figure demonstrates the value of estimating the partner's behaviour and shows the advantage of game theory controller.

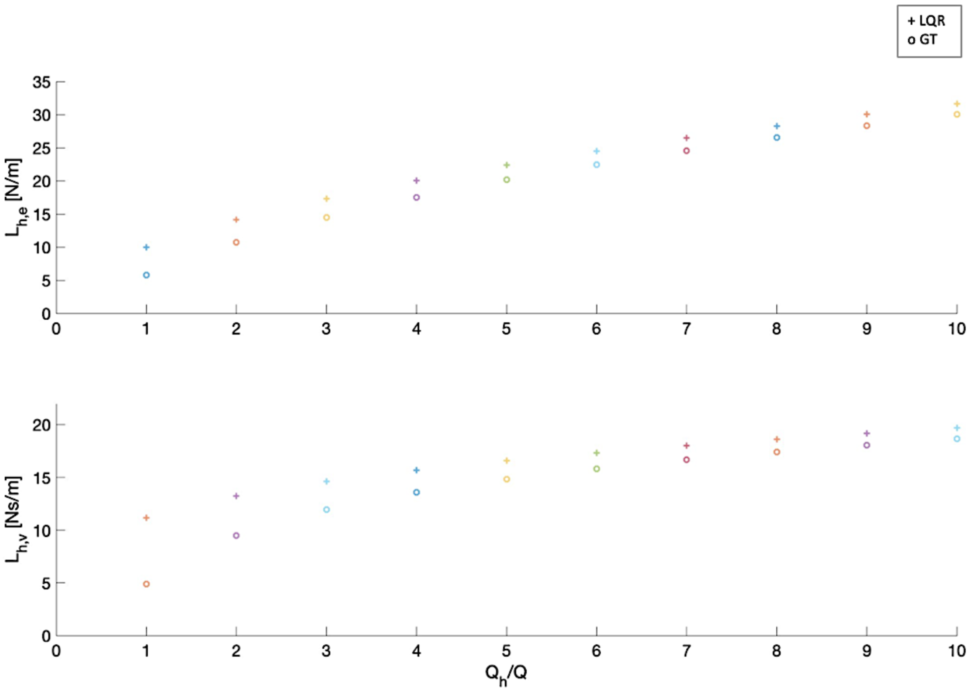

Figure 3.1. LQR vs game theory human gains.

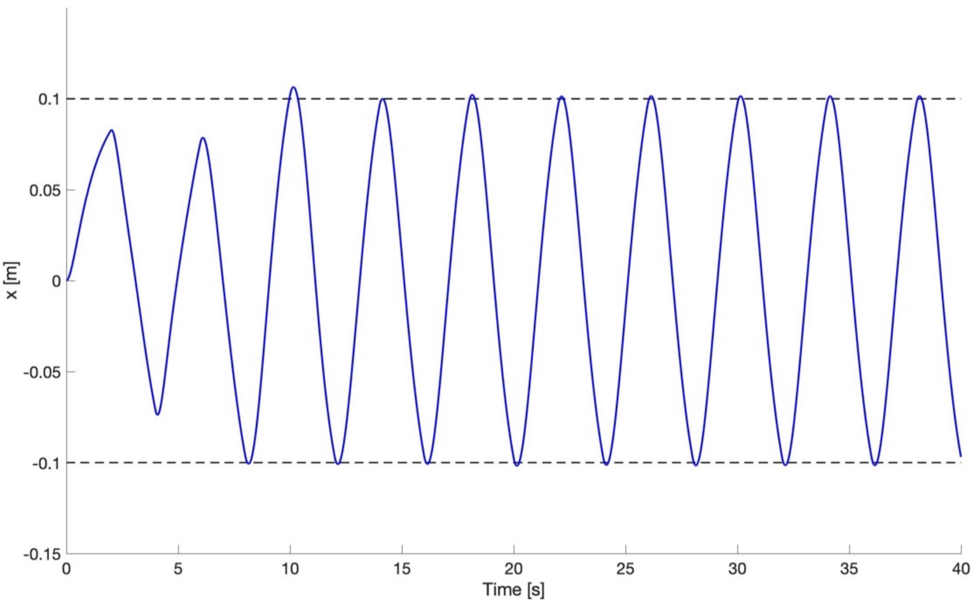

Figure 3.2. Position profile during the reaching task with a game theory interactive controller.

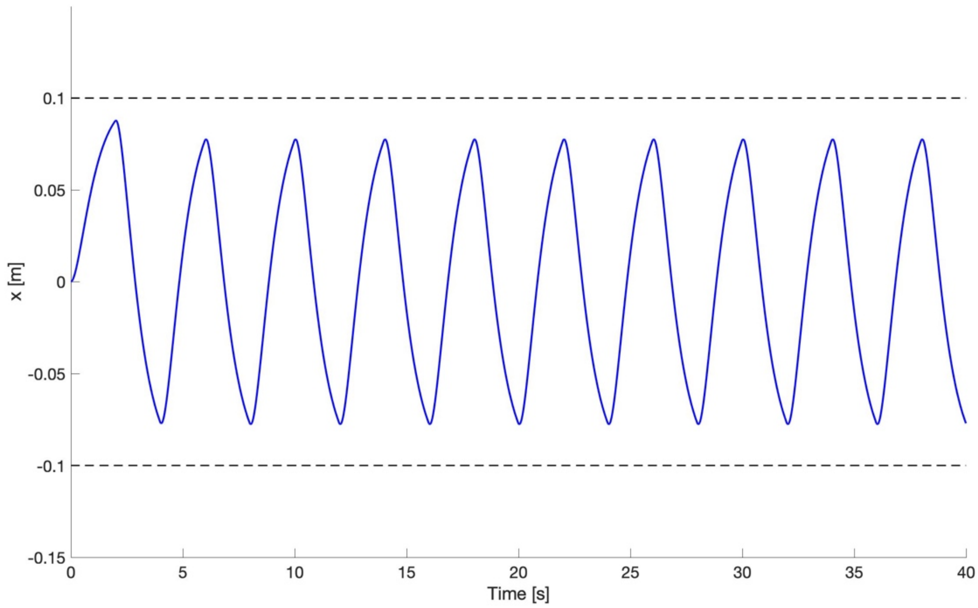

Figure 3.1. Position profile during the reaching task with two independent LQR.

Figure 3.2. shows the ability to fulfil the task in the collaborative case, i.e. with a game theory controller and *figure 3.3.* shows how in the co-activity case, the task is not successfully achieved. Although the arm does correctly the back and forth movements, it does not reach the desired positions. Both cases have been simulated with the same cost function and with the same Q and Q_h, to participate in the same task.

$$Q = Q_h = \begin{bmatrix} 100 & 0 \\ 0 & 0 \end{bmatrix}$$

To successfully achieve the target position, LQR human or robot state weights should be greater. If the simulation of an arm reaching the target position with two independent LQR is done with greater weights, the results are the ones shown in *figures 3.4* and *3.5.* In *figure 3.4.* the robot weight is $Q = \begin{bmatrix} 100 & 0 \\ 0 & 0 \end{bmatrix}$ and the human weight is $Q_h = \begin{bmatrix} 1000 & 0 \\ 0 & 0 \end{bmatrix}$, and in *figure 3.5.* the robot weight is $Q = \begin{bmatrix} 1000 & 0 \\ 0 & 0 \end{bmatrix}$ and the human weight is $Q_h = \begin{bmatrix} 100 & 0 \\ 0 & 0 \end{bmatrix}$.

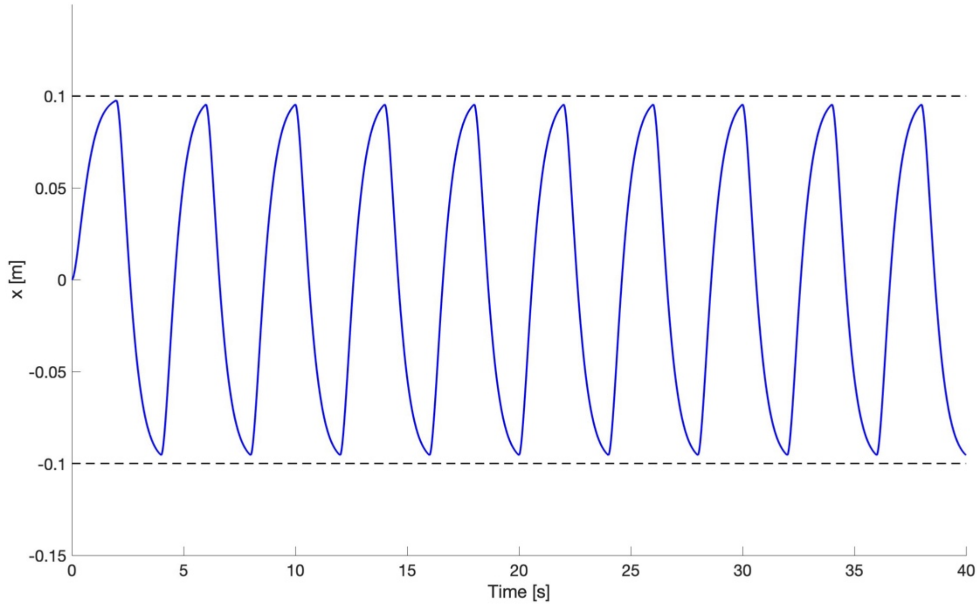

Figure 3.2. Position profile during the reaching task with two independent LQR with the human weight greater than the robot weight.

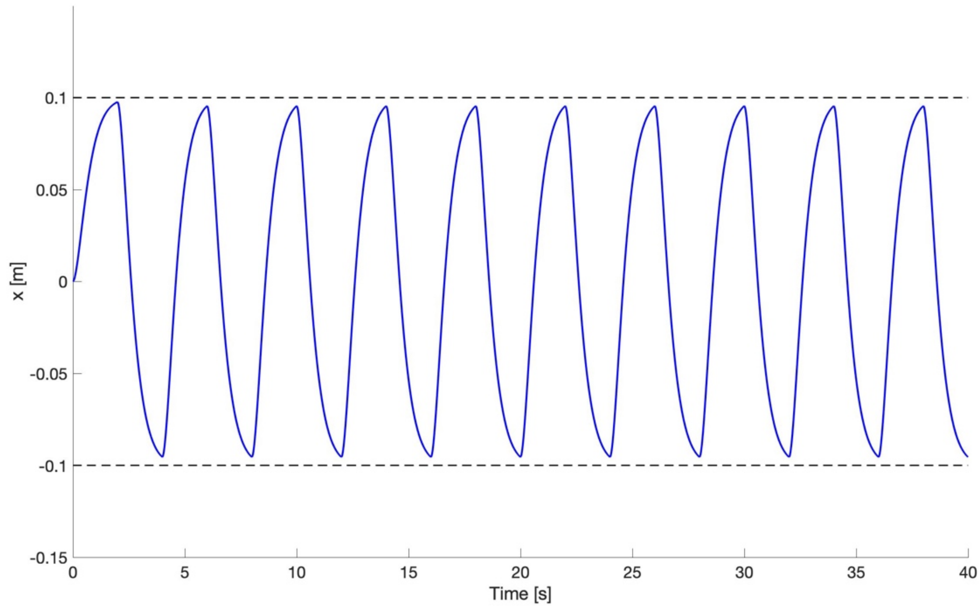

Figure 3.3. Position profile during the reaching task with two independent LQR with the robot weight greater than the human weight.

As it is seen in the previous figures, the task is successfully reached either if the human state weight is increased or if the robot state weight is increased. As both agents are simulated with the same cost function, both have the same influence when trying to do the task, so it is independent what weight is increased, whether the robot or the human weight, since in any case the specified task will be completed.

As in the co-activity case there is no interaction between agents and each one does not estimate its partner's behaviour, it can be seen how the human gains, i.e. the human effort, do not change during the performance, as the gains calculated initially with the Riccati equation are not updated because of the non-estimation of the partner's parameters. It can also be seen how the estimated human gains remain equal to zero, for the same reason of non-estimation between the agents. In the collaborative case (*figure 3.7.*), the estimated human gains converge in a few seconds to the real value. This is because during the first seconds, the real value and the estimation value are different from each other and the robot is estimating the human gain, i.e. the game theory algorithm is being applied. When both estimated and real values are the same, it is when the coordination between the agents is achieved. It can be seen how the estimation and the adaptation of the partners' parameters can induce the human to put less effort in reaching the task than in the co-activity case, where the effort has to be bigger.

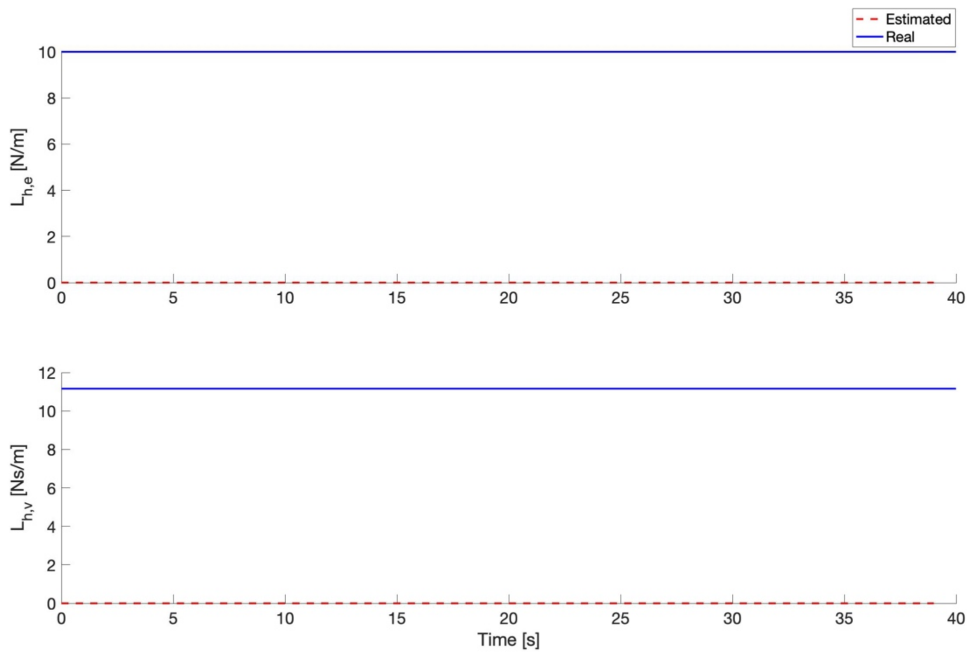

Figure 3.4. Human feedback gain with two independent LQR.

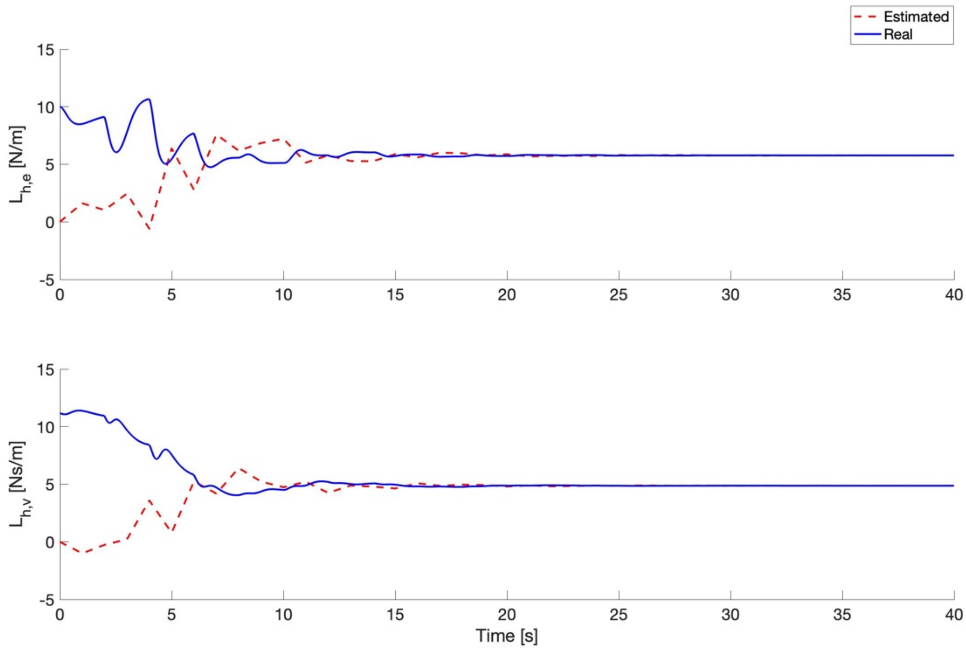

Figure 3.6. Human feedback gain with a game theory controller.

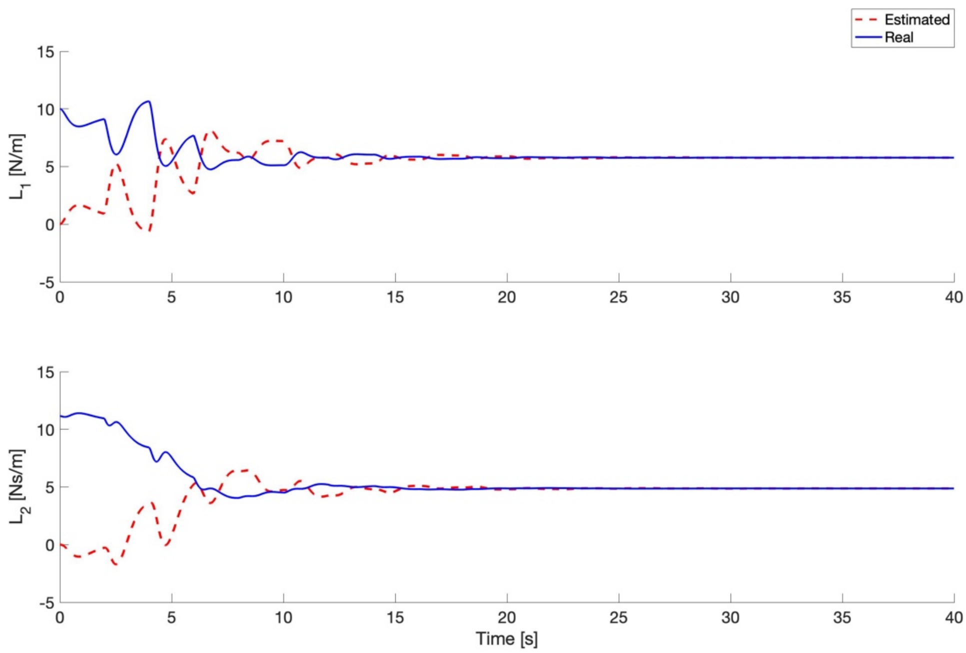

Figure 3.5. Feedback gain of the robot's control with a game theory controller.

In the last chapter, when all the interactive behaviours were introduced, the collaborative case was described as a symmetric behaviour. This symmetry in the behaviour can be seen by comparing the *figure 3.7.* and the *figure 3.8.* Both real values are exactly the same, although the each one presents the feedback gains of different agents (the robot and the human). This means that they have an equal distribution between both agents, and they provide the same effort to reach the task.

Once again, it can be seen in *figure 3.9.* how the estimation in the co-activity case is null, as the feedback gain of the robot's control remains equal during all the simulation and the estimated one remains null.

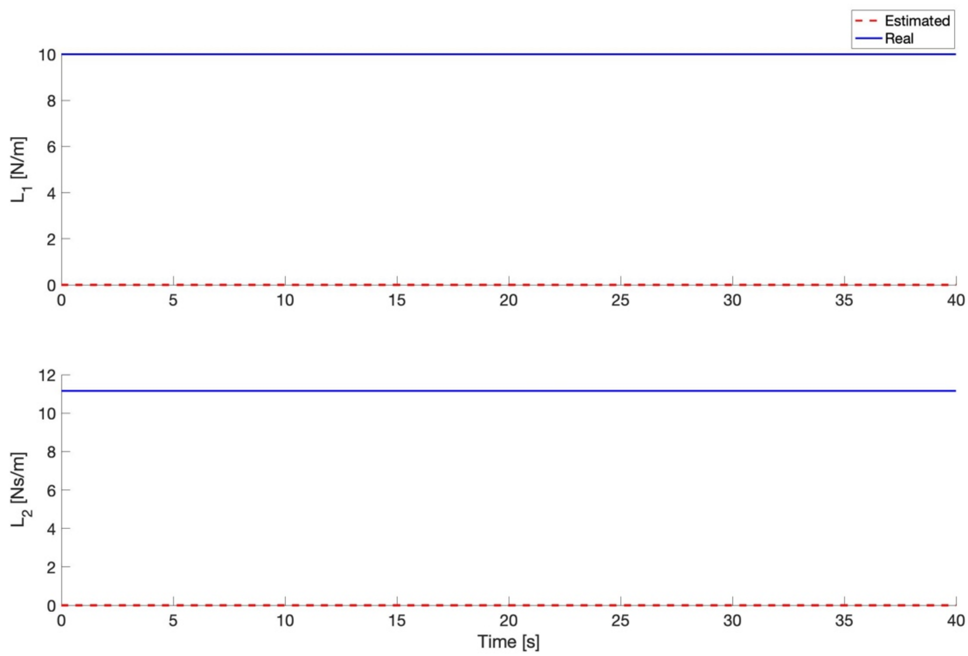

Figure 3.7. Feedback gain of the robot's control in co-activity.

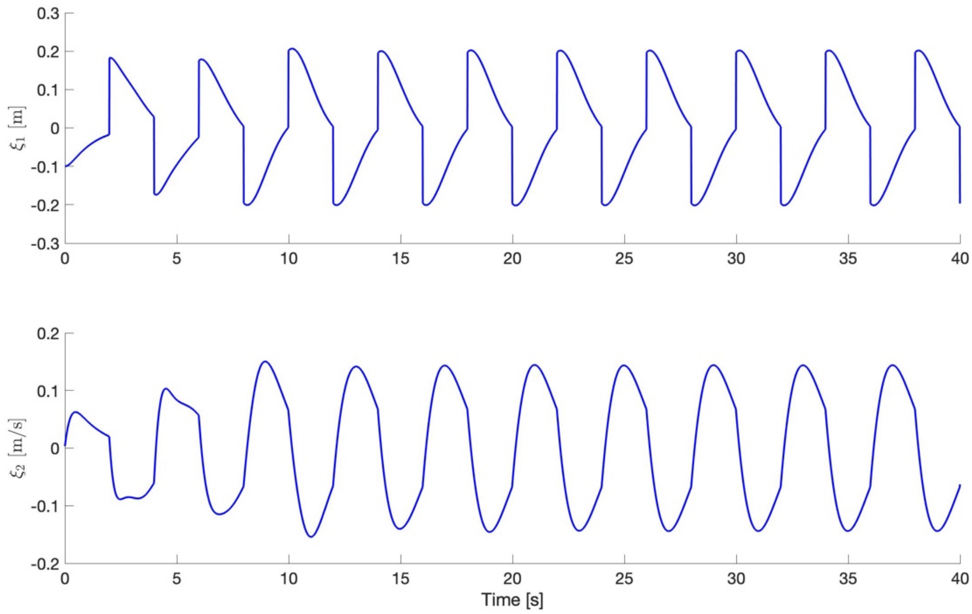

Figure 3.8. System state with a game theory controller.

The previous figure (*figure 3.10.*) shows the two components of the state (ξ) in the collaborative case. The upper component, which corresponds to the position error ($x - x_d$) has an asymptotical increase or decrease in the points where the target position goes from -10 cm to 10 cm or inversely. This is because when the arm reaches the desired position, the position error is zero, but just at the time the target position is reached, the target position changes to the opposite value, and then the position error is maximum. Apart from the asymptotical change, the other changes that are experienced in the position error are lineal, as the trajectory increases in a lineal way and so the error does decrease lineally. As it was seen in *figure 3.2.*, during the first few seconds the desired position is not yet reached. That is why in the first seconds neither the first component of the system state nor the second one do reach its maximums. The second component corresponds to the end effector velocity ($\dot{x}$). The velocity is null when the arm reaches the desired position, as the arm changes the direction of the trajectory.

3.2. COOPERATION

As it is said before in this thesis, there are two types of cooperative behaviours: assistance and assist-less-than-needed. Both of them have been proved in the simulation, and the results are the ones that are shown below.

3.2.1. Assistance

To evaluate if the game theory controller is able to adapt to any human's condition, it is simulated a scenario with five trials where the human is recovering its motor condition and the robot gives assistance. It is simulated that the human increases its strength, i.e. its state weight, trial after trial as simulating an improvement in its motor condition. When this happens, it will be seen down below how the robot is able to adapt to the new Q_h and, subsequently, it adapts its own state weight.

To simulate the assistance scenario, it is implemented in the code the sharing rule ($Q + Q_h \equiv C$). As in this case it is the human who recovers strength and increases gradually his or her weight, the sharing rule is implemented in the code in such a way that it is the robot who will adapt to the new human state weight ($Q = C - Q_h$). In this case, it is simulated that initially, the human has a weight of $Q_h = \begin{bmatrix} 25 & 0 \\ 0 & 0 \end{bmatrix}$ and the total contribution between both agents has to be $C = \begin{bmatrix} 200 & 0 \\ 0 & 0 \end{bmatrix}$. As it can be seen in the figures down below, in the first trial (which is shown in dark blue) the weight of the human is very close to zero, which means the human does not have almost strength to achieve the task. In this case, as it can be seen in *figure 3.12.*, the robot provides much more strength in order to complete the total contribution between both agents. As the patient recovers his or her strength, which is represented by increasing the contribution of his or her weight, the robot decreases the strength provided. Thus, it provides just the strength that the human needs to fulfil the task. This is shown in the figures down below.

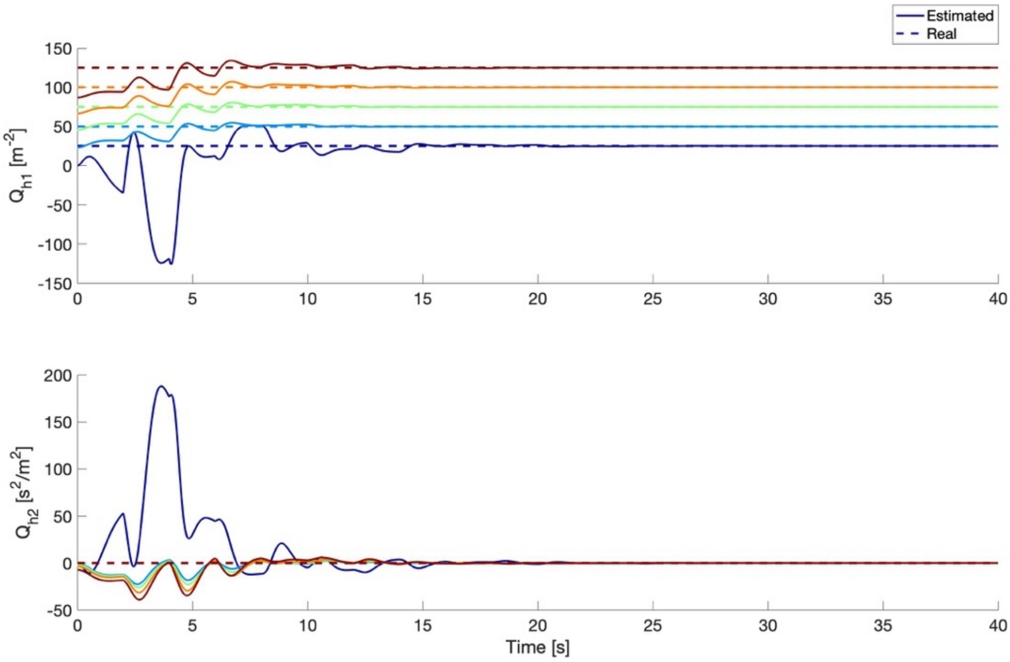

Figure 3.10. Human state weight Q_h in assistance.

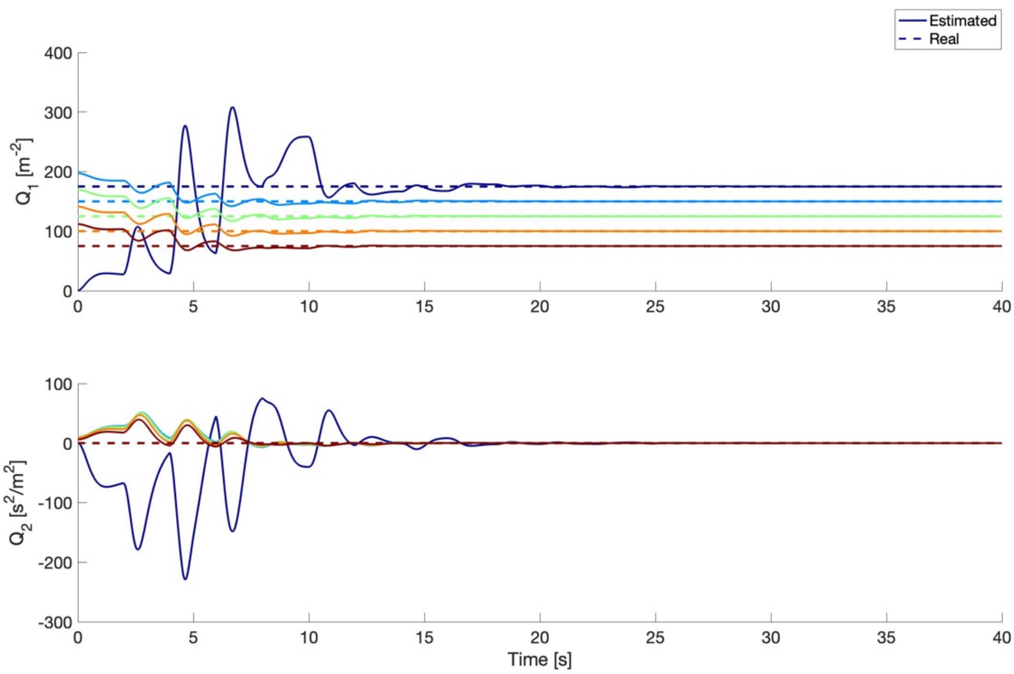

Figure 3.9. Robot state weight Q in assistance.

It is presented in *figure 3.13.* that in every trial the target position is achieved and the trajectory remains similar, despite the switch of contribution to the task between the human and the robot.

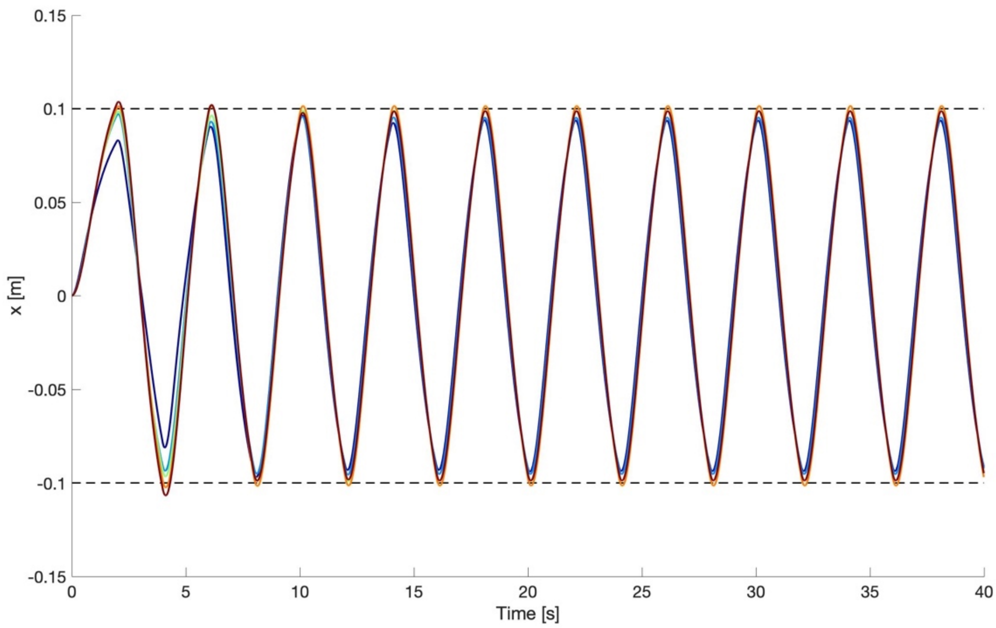

Figure 3.11. Position profile during the reaching task in assistance.

The next two figures (*figure 3.14* and *figure 3.15*) show the human's and the robot's efforts to reach the task during the five trials. It can be seen how the effort done in the first trial by the human (the one that is represented in dark blue) is almost null, so the effort that has to do the robot to fulfil the task is really elevated. As long as the patient recovers strength, he or she can also put more effort in the task, so the robot decreases its effort in order to provide just the assistance that the human needs.

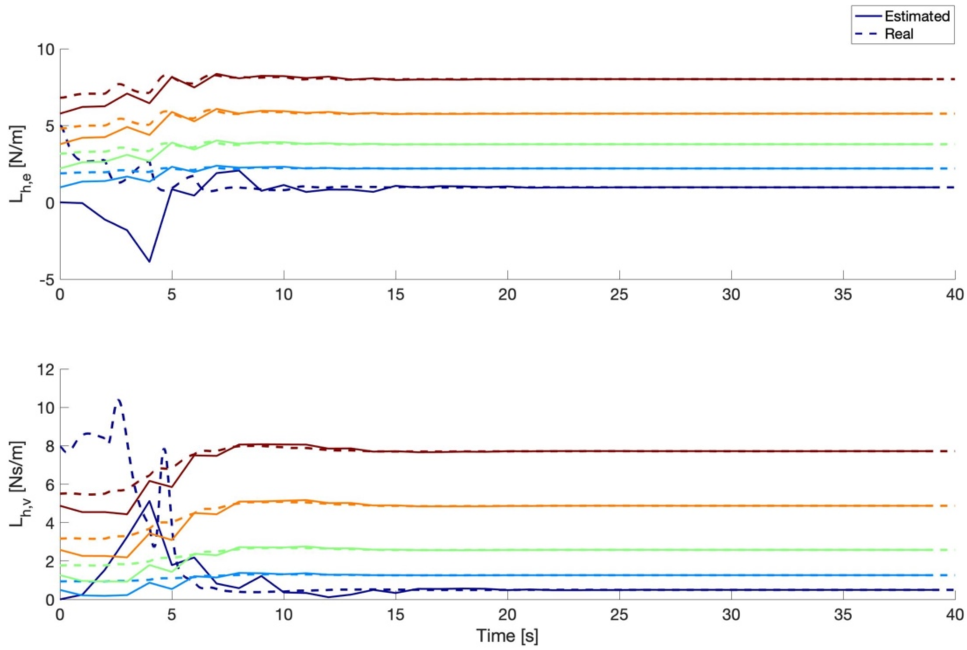

Figure 3.12. Human feedback gains in assistance.

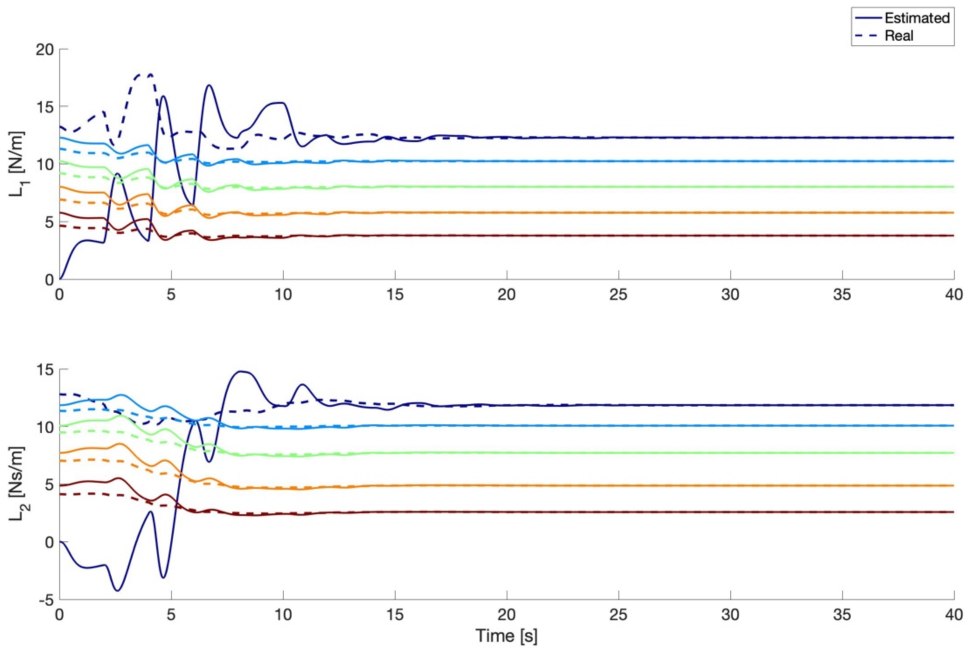

Figure 3.13. Feedback gain of the robot's control in assistance.

3.2.2. Assist-less-than-needed

To simulate assist-less-than-needed, it is necessary to set C to make the robot unable to reach the task alone, so that the human has to increase his or her effort to fulfil the task. Unlike in the previous case, here it is not the human that decides to increase his or her weight, but the robot that decides to give less assistance than what the human needs in order to motivate him and prevent him from slacking. In this case, at each iteration the sharing rule is computed as $Q_h = C - Q$. In the simulation shown below, the parameters set were $Q = \begin{bmatrix} 50 & 0 \\ 0 & 0 \end{bmatrix}$ and $C = \begin{bmatrix} 200 & 0 \\ 0 & 0 \end{bmatrix}$, so it was required for the human to contribute in the task with a big weight in order to accomplish the sharing rule.

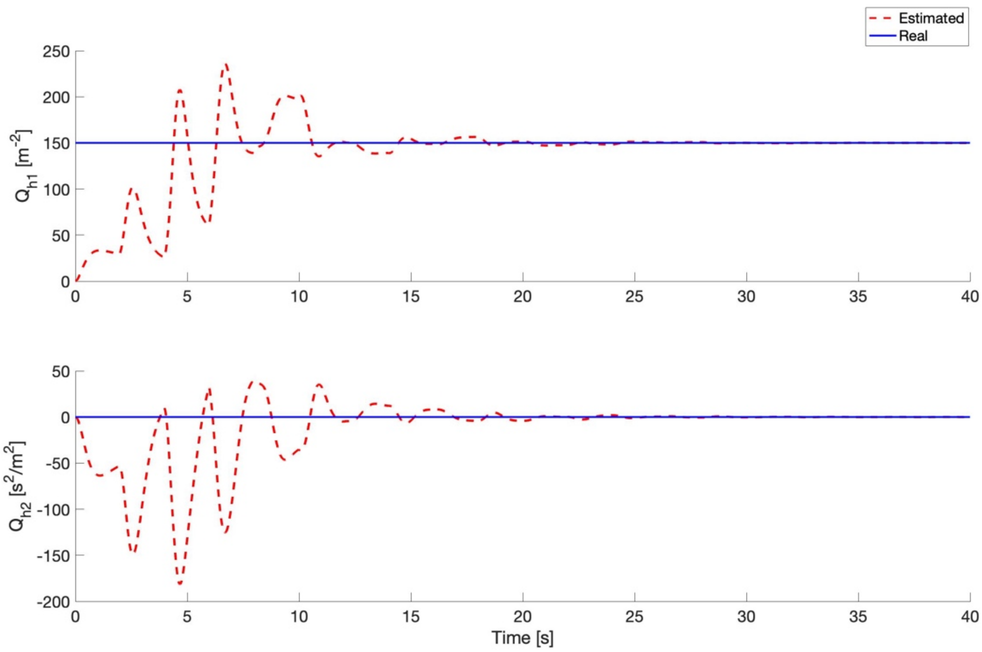

Figure 3.14. Human state weight in assist-less-than-needed.

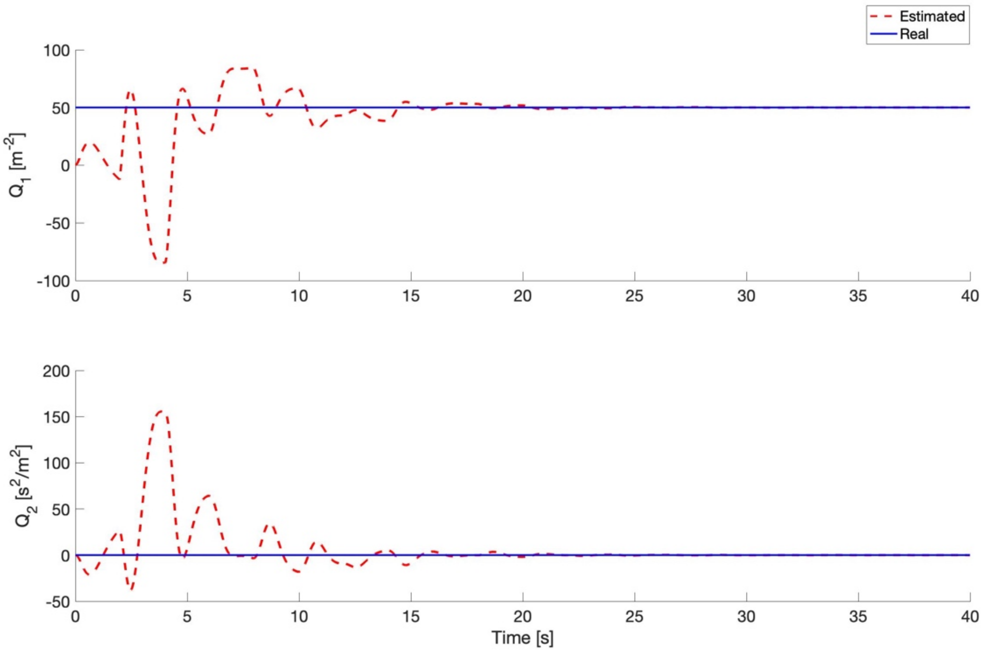

Figure 3.15. Robot state weight in assist-less-than-needed.

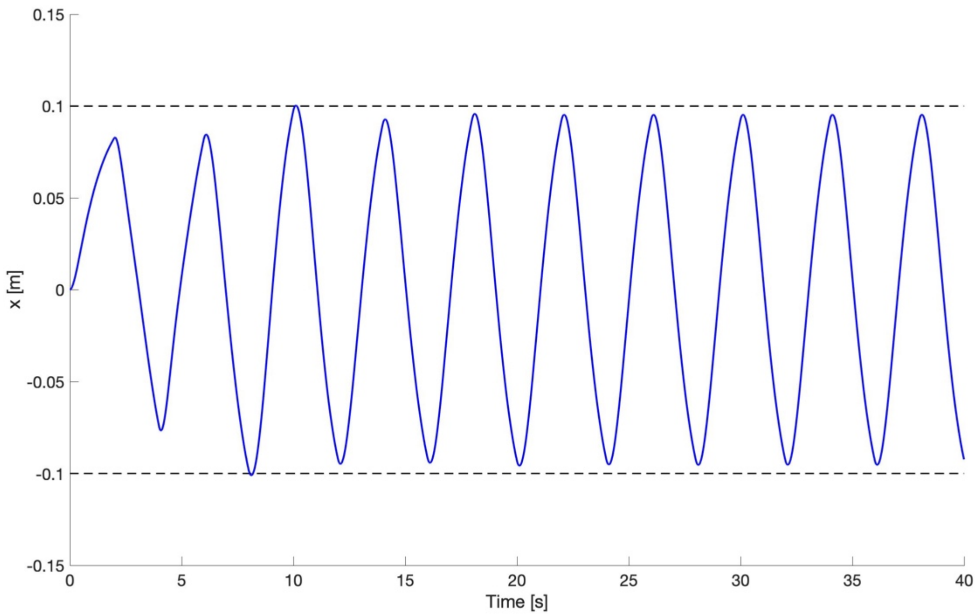

Figure 3.16. Position profile during the reaching task in assist-less-than-needed.

It can be seen in *figure 3.18.* how the task is successfully fulfilled when the robot is giving less assistance than needed to the patient.

3.2.3. Inconstant recovery

Another case to study from cooperation is when the recovery of the patient is inconstant. The motor behaviour of a stroke survivor may not be gradual and always improving. To prove the adaptability of the controller in the case in which the user has an irregular progress and sometimes its progress takes a step back, it is simulated a human user with a random state weight. It is demonstrated that the robot adapts its state weight whether the progress is gradually or not and helps the human to fulfil the task.

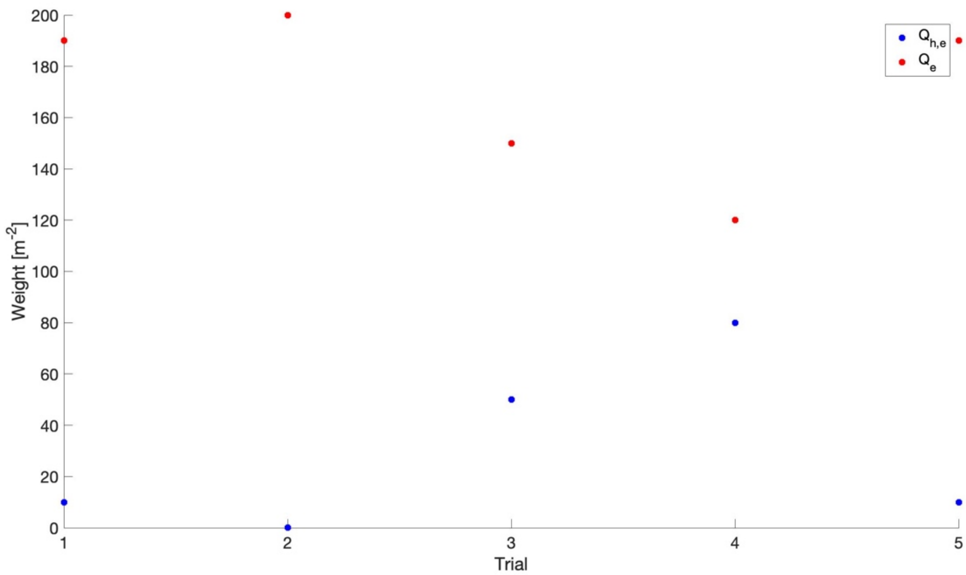

Figure 3.17. Human (represented with blue dots) and robot (represented with red dots) state weights when the progress is inconstant.

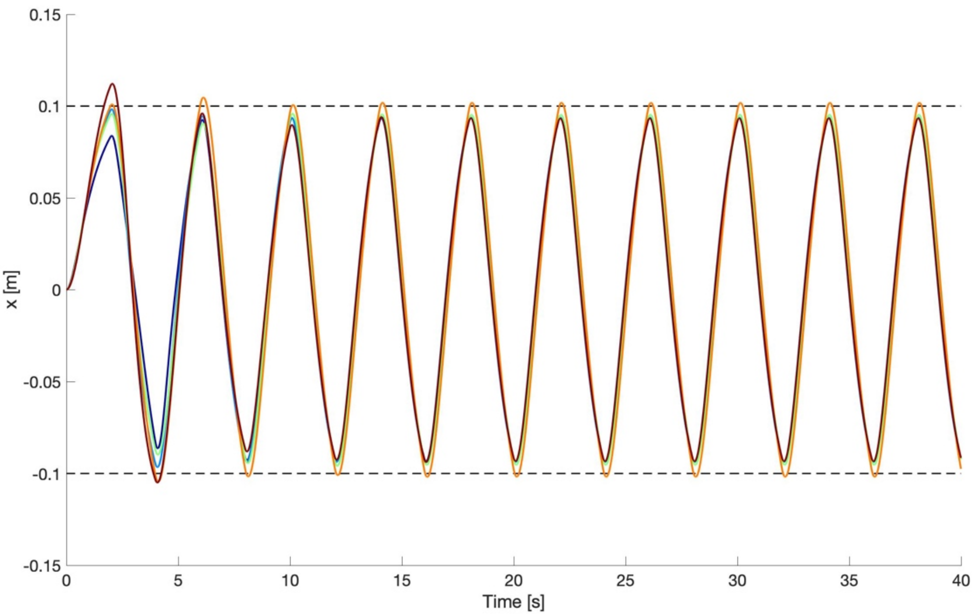

Figure 3.18. Position profile during the reaching task when the progress is inconstant.

As it can be seen in the previous figures, the robot is able to adapt to an inconstant progress of the human and the task is successfully fulfilled.

3.3. COMPETITION

This type of interactive behaviour is reached when the robot provides resistance instead of assistance, and this can be done by setting its state weight negative ($Q < 0$). Unlike what is expected, seeming that competition between a robot and a human can be harmful for the human, it is desirable to have competition to let the human try to improve performance and be involved in the training. This type of competition will promote active learning, which will help the human to improve his or her motor capability, but will not force the patient.

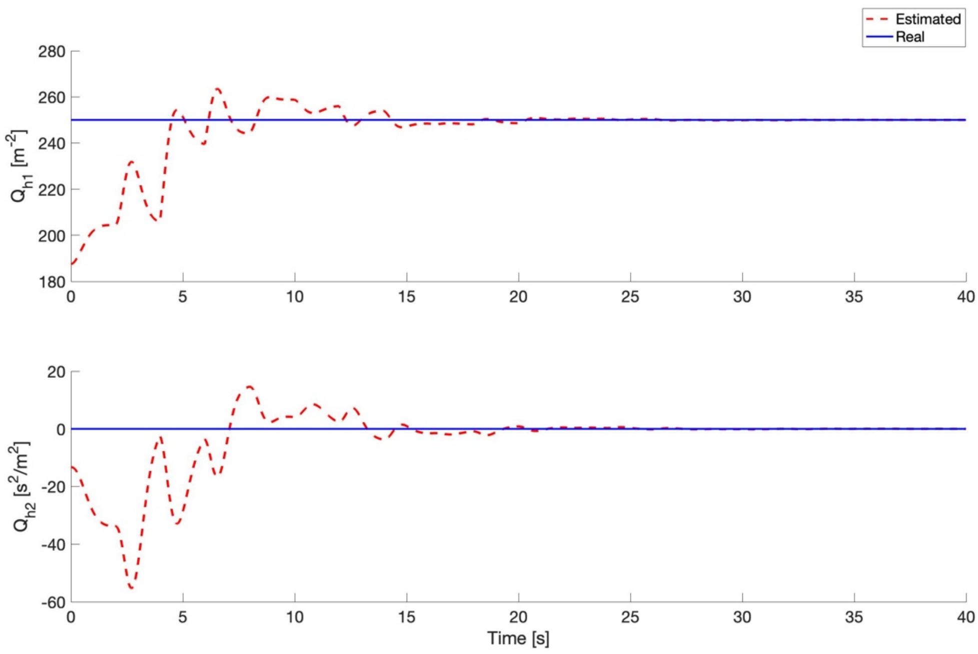

Figure 3.19. Human state weight in competition.

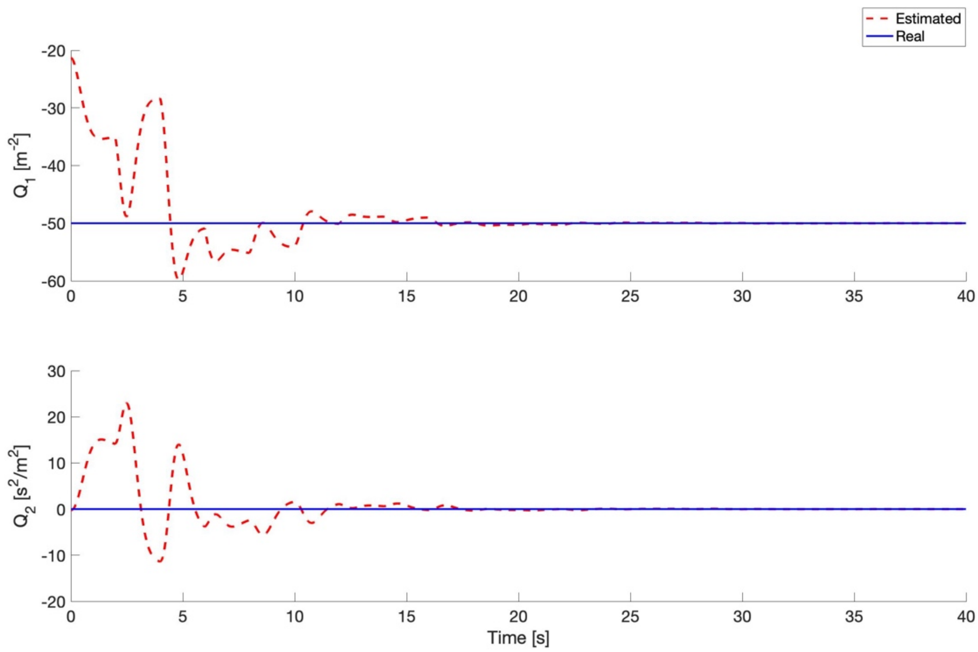

Figure 3.20. Robot state weight in competition.

It is shown in the figures above that the robot state weight is defined negative, so the human has to increase his or her strength in order to reach the target position and overcome the resistance that the robot is providing.

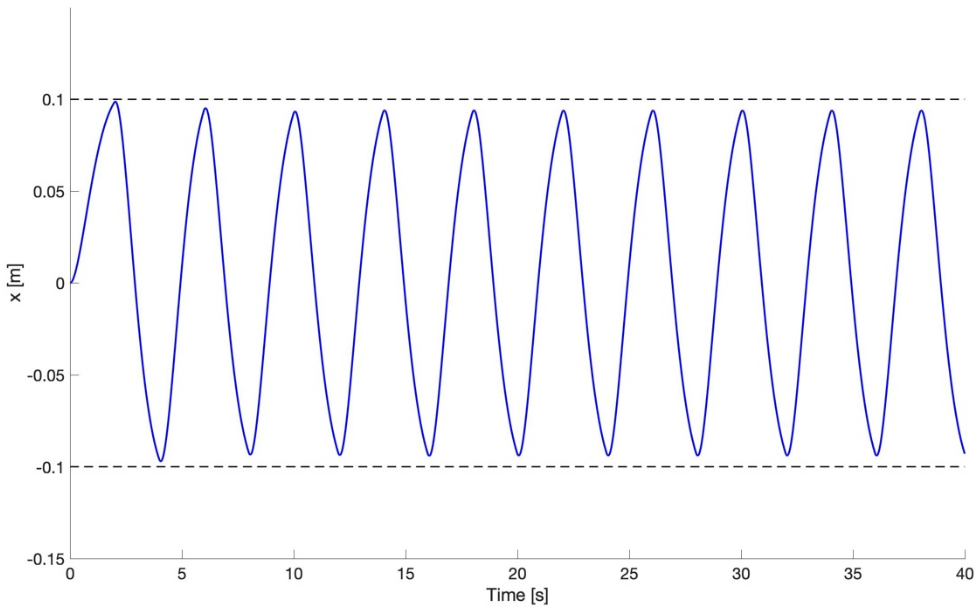

Figure 3.21. Position profile during the reaching task in competition.

With this type of behaviour, the task is successfully reached too.

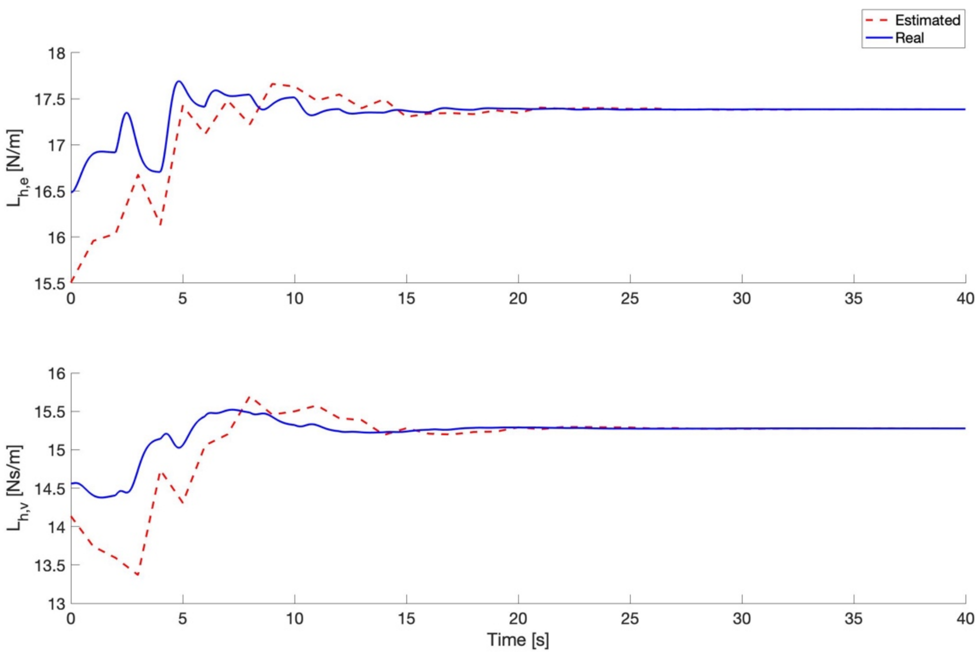

Figure 3.22. Human feedback gain in competition.

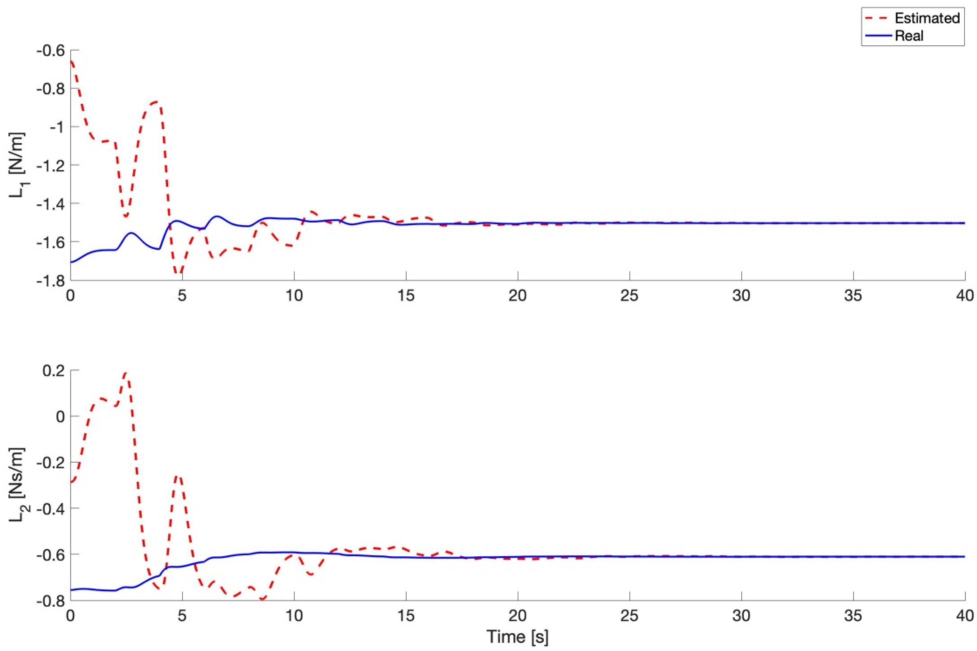

Figure 3.23. Feedback gain of the robot's control in competition.

The above images show how it is possible to reach the goal when the robot is causing resistance, i.e. it is trying to keep the human away from reaching the target position: the human puts much more effort than in the collaborative case, for example, and this is done to compensate the robot's negative gain.

4. DISCUSSION

In this thesis, it has been presented a framework for interaction control of rehabilitation robots. The main idea was to define the rehabilitation robot's control and its human user's control through its respective cost functions. Using this framework, different types of interaction strategies have been implemented and tested.

The different types of interaction strategies that have been tested in the game theory framework are the competition type of interaction behaviour, which can be used to challenge trainees thus keeping them engaged in training; collaboration, in which both agents have the same goal and share the effort to reach it with no role distribution; and cooperation, which has a role distribution through sharing the effort done by each agent and has two ways of performing it: assistance, which provides just enough assistance to succeed in the reaching task by sharing the trainee's effort, and assist-less-than-needed, which provides less assistance than what the patient needs to try to keep him or her engaged in the task and prevent him or her from slacking off. Another type of interaction behaviour that has been tested is co-activity, which does not involve game theory, as it is performed as an interaction where the agents do not estimate their partner's behaviour, so both agents are modelled as two independent LQR.

The critical part of the algorithm for implementing the game theory framework consists of the identification of the human users' control, which is necessary in order to consider it adequately. Simulations have demonstrated the stability that the game theory controller provides to the trainee, its reactivity and the behaviour adaptation to the partner's control dynamics.

Contact robots interacting physically with humans during rehabilitation therapies are increasing year after year. Typical rehabilitation robots usually use a controller that does not consider the user [3]. As it has been described in this thesis, this type of human-robot interaction is denominated co-activity. This type of interaction does not involve the robot observation of the human's behaviour and it works as long as the robot's task corresponds to the human's task. This interaction behaviour, where the robot ignores the human control, is useful for specific tasks, but using other types of interaction strategies can guarantee a more versatile and flexible interaction combining the partners' capabilities [46]. These strategies need a process to understand the partner's control.

To study this versatile interactive control, this thesis has simulated the human-robot interaction, where two physically connected agents have to understand each other's control and update their own control in order to successfully reach a task together. This simultaneous partner's control identification and adaptation has been guided by the research made in [1]. It has been proved that with the integration of game theory, the adaptive controller provides a stable solution, can identify the partner's control law and is able to minimize the individual cost in both agents in the sense of Nash equilibrium [1].

The results from the simulation done in the thesis show that the method proposed in [1] allows the robot and the human estimate each other's cost function during interaction, as well as to adapt their control to fulfil the common task. The simulation results also manifest that the adaptive game theory controller can implement different interactive behaviours of physical interaction between two agents.

Could it be considered that a game theory controller is better for rehabilitation robots than an LQR controller? It has been seen in the results of the simulations that the task was successfully reached when simulating the rehabilitation robot and the human trainee as two independent LQR controllers and when simulating them as interactive game theory controllers. Although the task has been successfully carried out in both cases, it has been seen in the results of the simulations that with the game theory controller, the effort that the human has to put to perform the task is less than in the case in which both the robot and the human are modelled as two independent LQR.

With the argument given in the previous paragraph, it can be determined that the game theory controller is a good option to implement it in a rehabilitation robot. Its main strengths are the following ones:

i. As the robot estimates the behaviour of the human, it allows the human to put less effort to reach the goal. This allows the patient to have a rehabilitation adapted to their abilities and to their strength.

ii. The simulations have demonstrated the stability and the optimality provided by the game theory controller.

iii. The game theory controller is able to perform different interactive behaviours. It is able to provide less assistance than needed when it is necessary to motivate and keep the patient engaged in the rehabilitation and it is also able to provide the necessary assistance that the patient needs when his recovery is not gradual. This is only possible when the robot estimates the behaviour of the patient, as it knows what the human needs at each moment.

For all these reasons, it is illustrated that the presented algorithm can be used as a dynamic framework for the rehabilitation of impaired humans, for example for users recovering after a stroke.

5. FURTHER WORK

In this chapter will be described the possible studies or implementations that could arise from the study done in this thesis. All of them are only options that are thought to be useful to investigate, but it must be said that they have not been tested during the development of the thesis and its possible applicability is not known. These possible advances are:

i. Implementation of the game theory controller in a real rehabilitation robot.

The main advance that could derive from the study made in this thesis is to implement the game theory controller in a real end-effector rehabilitation robot. This implementation is done in [1] in an end-effector device. It was tried to implement it in Reaplan, the rehabilitation robot developed in the *Université Catholique de Louvain*, but unfortunately it has not been achieved. Based on the experience of trying to deploy from the simulation to the experimental case, some guidelines to do it will be provided.

In the simulation, it has been modelled the human's motor control as a game theory controller. Does it mean that when implementing the game theory controller in a real rehabilitation robot, the human's motor control has to correspond to game theory? It is unknown if the human central nervous system behaves as predicted by game theory to physical interaction [1], but there is evidence that it considers the partner's sensorimotor control during the performance of a common task [46].

When it comes to implementing the controller in a real rehabilitation robot, it must be borne in mind that the behaviour of the human user should not be simulated, since this behaviour will be performed by the real patient who will be doing rehabilitation exercises with the robot. Thus, not all the equations that have been explained in the second chapter have to be taken into account; the ones that simulate the human's behaviour do not have to be implemented in the real robot, only the ones that estimate it.

When the experiment is done with a real robot and a real human user, the position and the velocity of the end effector are measured by the robot's sensors. Once the position and the velocity have been measured, the state of the system can be formed and from here start the process described in the methods chapter.

One thing to keep in mind that changes when trying to implement the controller in a rehabilitation robot instead of just simulating it, is that only the robot has to estimate the behaviour of the human user; the estimation of the robot's behaviour by the human trainee should not be taken into account, since it is a real user. Thus, the resulting equations for determining the robot motor command and the estimation of the human motor command are the following ones:

$$\dot{\xi} = A\xi + B(u + u_h), \qquad \xi = \begin{bmatrix} x - x_d \\ \dot{x} \end{bmatrix}$$
$$A \equiv \begin{bmatrix} 0 & 1 \\ 0 & -I^{-1}D \end{bmatrix}, \qquad B \equiv \begin{bmatrix} 0 \\ I^{-1} \end{bmatrix} \tag{10}$$

The system state is computed the same way, with the difference that the position and the velocity will be measured by the sensors of the real robot.

As it is not known neither the weight of the human nor its motor command, the cost functions of both agents will be:

$$U = \int_{t_0}^{\infty} (\xi^T Q \xi + u^T u)\, dt$$
$$\widehat{U}_h = \int_{t_0}^{\infty} \left(\xi^T \hat{Q}_h \xi + \hat{u}_h^T \hat{u}_h\right) dt \tag{11}$$

In these equations, each agent fulfils the task by minimizing the error to the target while using a minimal metabolic cost. For computing the Riccati solution, the coupled equations are the following ones:

$$A_r^T P + P A_r + Q - P B B^T P = 0_{2n}, \qquad A_r \equiv A - B\hat{L}_h \tag{12.1}$$

$$L \equiv B^T P \tag{12.2}$$

$$u = -L\xi \tag{12.3}$$

$$A_h^T \hat{P}_h + \hat{P}_h A_h + \hat{Q}_h - \hat{P}_h B B^T \hat{P}_h = 0_{2n}, \qquad A_h \equiv A - BL \tag{13.1}$$

$$\hat{L}_h \equiv B^T \hat{P}_h \tag{13.2}$$

$$\hat{u}_h = -\hat{L}_h \xi \tag{13.3}$$

After computing this, the state estimation and the state estimation error are updated, the estimated Riccati equation for the human is updated and, in the case of cooperation, the sharing rule is applied:

$$\dot{\hat{\xi}} = A\hat{\xi} + B(u + \hat{u}_h) - \Gamma\tilde{\xi}, \qquad \tilde{\xi} \equiv \hat{\xi} - \xi \tag{14}$$

$$\hat{P}_h \equiv \alpha(\tilde{\xi} - \xi)\xi^T \tag{15}$$

$$Q + \hat{Q}_h = C \tag{16}$$

The proposed algorithm for implementing the controller and carrying out the experimental case with stroke survivors is the following one:

Algorithm

Inputs: Current state ξ, target position x_d

Outputs: Robot's control input u, estimated human's cost function weight $\hat{Q}_h$

begin

- Define the target position x_d
- Initialize $Q, \hat{Q}_h, u, \hat{u}_h, \hat{\xi}, \hat{P}_h$
- Set the parameters Γ, α, C (in the case of cooperation) and the time of one trial t_f
- **while** $t < t_f$ **do**
  - Measure the position x and the velocity $\dot{x}$ and form the state ξ
  - Calculate the state estimation error $\tilde{\xi}$ and the estimated state $\hat{\xi}$
  - Update $\hat{P}_h$ and compute the estimated human's control gain $\hat{L}_h$ and the estimated human's motor command $\hat{u}_h$
  - Solve Riccati equation and compute the robot's control input u
  - Calculate the estimated human's cost function weight $\hat{Q}_h$
  - In the case of cooperation, adapt the corresponding cost function weight with $Q + \hat{Q}_h \equiv C$

Figure 5.1. Proposed algorithm for doing the experimental case.

ii. Simulation of the human-robot interaction in the game theory framework in an assistive robot

The goal of rehabilitation and assistive robots is to achieve the best possible motor functional recovery for people with impairments due to diseases as stroke. In this thesis, a simulation of the interaction between the human and the robot has been developed within the framework of game theory, assuming that the robot is a rehabilitation robot, that is, a robot that is used as therapy aid, instead of assistive device. One possible study that would be interesting to do is to try to implement either the simulation or the experiment in assistive robots. The goal of assistive robots, instead of being a tool used for therapy, is to support independent living of people who have chronic or degenerative limitations in motor abilities [47]. An assistive robot performs a physical task for the well-being of a person with a disability, with this task embedded in the context of normal human activities of daily living [48]. It would be a great advance for the welfare of people with mobility problems who need assistive robots to carry out their activities of daily life to have a robot able to understand their behaviour and react in an optimal and effective way to it.

Although it sounds like a great idea, it would not be an easy task to carry out. There are many differences between implementing it in a rehabilitation robot and an assistive robot. In a robotic therapy, the injured patient performs arm exercises such as the suggested in this thesis, going from one desired position to another. The rehabilitation robot, through its screen, tells the human what task he or she should do and the human performs it in a repetitive way. In the case of the assistive robot, there is no pre-established task. The human user performs his day-to-day tasks, but the robot does not know what his final goal is. Thus, in the equations for implementing it there would not be a target position (x_d), so the state ξ could not be able to track the position error. It should be necessary to find a different way to find a solution for implementing it.

iii. Simulation of other types of trajectories instead of point-to-point

In the simulation framework, it could be interesting also to prove whether the game theory controller also provides stability when the human does other types of trajectories. The trajectory tested in this thesis consists in basic point-to-point arm movements. Having in consideration other trajectories corresponding to tasks of daily life could be beneficial for post-stroke rehabilitation and it would be interesting to corroborate if also in other trajectories is obtained the stability and optimality with the game theory controller as well as in the simulated trajectory in this thesis.

6. BIBLIOGRAPHY

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