A Force-Sensorless Controller Approach
towards Assisted Human-Robotic Load Co-manipulation

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Preface

To be honest I am not so keen on long elaborate prefaces in a thesis for completion of the masters degree. I sometimes feel it is a little bit over the top for a years work. Nevertheless, I did feel the need to shortly express my gratitude to the ones that supported and guided me throughout my graduation.

When, mostly spontaneous, meeting with Stefan, I always felt welcomed when he enthusiastically started the conversation with asking me ‘How are you doing’, which I on my turn gratefully used to start the discussion about the current research challenges at hand. Many times this resulted in lively meetings, ending with new insights and possible directions to follow for which I’m thankful. I also shortly want to thank Jurjen here, that, as a colleague of Stefan, many times enthusiastically got involved in our discussions and shed some new insights on subjects.

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As a student of professor Nijmeijer I also had the structural monthly meetings at his office. I appreciated this way of keeping contact and thereby ensuring sufficient and proper progress of my graduation. Many times I experienced the monthly meetings as a kind of ‘think thank’ where, sometimes even with a big smile, possible solutions for challenges faced were being discussed. By being critical professor Nijmeijer was able to give guidance to my work, which gave me a feeling of the tutor and his apprentice. I am thankful for this, as I am sure that his supervision accelerated my personal growth during my graduation.

Last, without mentioning them all by names, I want to show my appreciation to all those, friends, family and colleague students, that supported me throughout my graduation and helped me to keep on performing at my best.

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Abstract

Nowadays the involvement of robotics in human life is rapidly increasing. However, there still exist several difficult tasks a robot can not handle fully autonomous and many challenges to be overcome first remain. In the meanwhile human-robotic collaboration or co-manipulation is the alternative. While the human operator provides the required intelligence, the robotic system provides the required assistance. For example, when a human operator has to transport heavy loads the human operator provides guidance to the load while the robot provides force assistance for carrying. In this work, the focus lies in the design and development of a force-sensorless control strategy that can provide scaled human power assistance by means of a robotic device, while carrying unknown loads.

Literature shows great interest in human-robot cooperation. Subjects like for example human-robot interaction possibilities or programming robotic react behavior a priori receives attention. Also force support provided by robotic devices is known, only most are based on force-sensor information which is not desired due to for example costs and vulnerability.

This work handles two control approaches that amplify a human operator's force applied on an unknown load. The first is a robust control strategy earlier proposed in another work. The control strategy as newly proposed by this report is of the adaptive kind. Both work in a repetitive cyclic fashion consisting of two phases. The robust controller estimates the human operator's force by applying a negative feedback in the first phase and provides a scaled version of the estimate in the second phase. The adaptive controller quantifies the human operator's intention by an acceleration estimate in the first phase. Based on this acceleration estimate the controller adapts a loads' mass estimate in the second phase. By using this mass estimate a model calculates the scaled human force to be applied.

The performances of both controllers are evaluated by means of simulation and experiments. Simulations showed that in theory both controller approaches can provide scaled force assistance despite an unknown load. Based on the experimental results some important conclusions can be drawn. Both controllers depend on feedback estimates like velocity and acceleration. To obtain these, differentiation of position measurements is required which amplifies measurement noise. Therefore low-pass filtering is required but this introduces delays. And it are these delays that revealed a contradictory demand, namely that if a phase transition has occurred the settling time of these feedback estimates has to be minimal to be able to still track the signals within the duration of the phases. This is a first problem that requires future research. Another result is that the pulse-width-modulation nature, i.e. the cyclic fashion, of the two controller approaches leads to strongly undesired vibrations that can be clearly felt and heard by the human operator. To solve this the frequency of the cycle period should be chosen sufficiently high, which will conflict with the contradictory demand of the previous conclusion as it decreases the time-span of the phases. A future challenge remains to find solutions for both, that is work at a high cycle frequency and still be able to obtain proper feedback estimates sufficiently fast.
# Contents

Preface iv  
Abstract vi

1 Introduction 1  
1.1 Motivation .................................................. 1  
1.2 Problem statement ........................................... 2  
1.3 Contribution of the thesis .................................... 3  
1.4 Outline of the thesis ......................................... 3

2 Literature review 5  
2.1 Introduction .................................................. 5  
2.2 Review on human-robotic co-manipulation .................. 5  
2.3 Review on external force estimation .................................................. 8  
2.4 Discussion in perspective of current research ................. 10

3 Control design for human-robotic co-manipulation 13  
3.1 Introduction .................................................. 13  
3.2 Problem statement including requirements and assumptions .................. 13  
3.3 Controller design ............................................. 14  
3.3.1 Design Negative Feedback Estimation Controller ................. 15  
3.3.2 Design Power Assisting Controller .......................... 18  
3.3.3 Timescale implementation .................................. 22  
3.4 NFE Controller versus Power Assisting Controller .................. 23

4 Analysis and comparison of controllers by simulation 27  
4.1 Introduction .................................................. 27  
4.2 The ideal case ................................................ 27  
4.2.1 Simulation results for the Negative Feedback Estimation (NFE) Controller .................. 28  
4.2.2 Simulation results for the Power Assisting Controller .................. 30  
4.2.3 Comparison of results .................................... 33  
4.3 The effect of friction disturbances .................................. 34  
4.3.1 Simulation results of the Negative Feedback Estimation (NFE) Controller .................. 35  
4.3.2 Simulation results of the Power Assisting Controller .................. 36  
4.3.3 Discussion ................................................ 36  
4.4 The effect of quantized position measurements .................. 37  
4.4.1 Simulation results of the Negative Feedback Estimation (NFE) Controller .................. 37

viii
## CONTENTS

4.4.2 Simulation results of the Power Assisting Controller .................................. 38
4.4.3 Discussion ........................................................................................................ 42

5 Proof of Concept by experimental implementation .............................................. 43
  5.1 Introduction ....................................................................................................... 43
  5.2 Experimental setup ......................................................................................... 43
  5.3 Experimental results NFE Controller .............................................................. 45
    5.3.1 Original controller trial .............................................................................. 45
    5.3.2 Adapted NFE Controller by lowering algorithm execution frequency .... 47
  5.4 Experimental results PAC .............................................................................. 47
    5.4.1 Original controller trial .............................................................................. 48
    5.4.2 Adapted PAC, by lowering algorithm execution frequency ................. 49
    5.4.3 PAC with acceleration sensor ................................................................. 52
  5.5 Discussion experimental results ...................................................................... 54

6 Conclusions and Recommendations ..................................................................... 55
  6.1 Conclusions ..................................................................................................... 55
  6.2 Recommendations .......................................................................................... 57

A Simulation results of other human force input signals. ..................................... 61

B Amplitude spectra for several testcases ............................................................. 63
Chapter 1

Introduction

1.1 Motivation

Nowadays the involvement of robotics in human life is rapidly increasing. Already since the early 1960s the first robotic systems have appeared in an industrial environment [33]. Tasks performed by robots in such an industrial environment are for example welding, grinding, painting, pick and place operations etc. Outside such industrial environments, the employment of robotic systems is rather limited. However, this is changing very rapidly. The first commercial service robots are already available, performing tasks such as for example lawn mowing, security surveillance or even providing social interaction. However, the tasks performed are still very limited, which is due to the fact that significant challenges still have to be overcome first. Industrial robots typically only perform relatively simple tasks in a clearly predefined manner. For new (e.g. domestic) applications, robots have to perform several tasks in a fully autonomous manner. Autonomous here means that the robot performs tasks without any human involvement or intervention. Robots acting in an increasingly autonomous manner is a trend clearly visible in robotic prototypes that come into existence around the globe. Creating a robot that can act in a fully autonomous fashion is an ultimate goal in robotics [15, 32]. For difficult tasks, however, this is a challenge that is not likely to be solved in the very near future [40].

An intermediate step will be the inclusion of a human operator in the control loop of the robot. Therefore the field of Telerobotics is addressed. In a telerobotic system the human operator plays an important role. He perceives information from a remote environment through a human system interface and acts accordingly by sending commands to the remote robotic device [10]. As a result the robot performs the task while the human operator is still in charge. Most likely the robot performs simple parts of the task autonomously. However, the complete task, which the robot is not able to handle fully autonomously yet, is still guided and controlled by the human operator. So-called Telepresence is one of the key factors here. Telepresence means that the information about the remote environment is displayed to the operator in a natural manner, which implies a feeling of presence at the site [10]. To create a good degree of telepresence, besides for example vision and auditory interfaces, a sense of touch is required. The sense of touch provided to the human operator can be divided in two main components: a tactile and a kinesthetic component. The first relates to initial interaction with manipulated objects and provides feedback about their texture, geometry or temperature. The second, kinesthetic feedback, provides information about pose and motion, contact forces, weight and object deformability. Integration of both components is generally known as haptics.
The Eindhoven University of Technology has started the project Teleman [40]. The aim of the Teleman project is to contribute to developing a new high tech industry for teleoperations. One of the main issues of this project is that the teleoperator they are aiming at is generic, meaning that it can be used in a variety of tasks. The research as discussed in this thesis is performed inside the Teleman project framework. Herein, a special interest in the interaction between a human operator and a robotic device is displayed.

More specific, the emphasis here is on human-robot co-manipulation of objects. Different kinds of human-robot co-manipulation research already exist. While some of these have a strong focus on the social interaction by means of vision and oral communication [7, 8], others have a strong focus on the load co-manipulation itself [26, 25, 45, 46, 2, 4, 21, 3, 22, 29, 5, 13, 24, 20, 14, 16]. In the latter, human-robot co-manipulation of loads, the exerted forces on the load are of significant importance. Therefore the current research objective is closely related to the haptic concerns of telerobotics and then especially to the kinesthetic interaction.

In the following section the problem statement will be discussed. Hereafter the contributions of this thesis will be elaborated in Section 1.3 and finally the outline of the thesis is presented in Section 1.4.

1.2 Problem statement

There are several situations where a human has to provide load transportation. Examples are airfield personnel putting heavy suitcases in racks, nurses moving patients, construction workers transporting and positioning heavy and large assembly parts at building sites, soldiers carrying heavy equipment etc. In some of these cases, the strength that a human can provide by himself is insufficient. However, autonomous robotic devices to take over these tasks are not readily available yet, since such load carrying where the trajectory is subject to changing environmental conditions requires a high level of intelligence. To cope with such a dynamic environment, a human operator is thus still necessary to interpret the situation and act accordingly. He needs to determine how the trajectory should be and where the load should be positioned. This reveals the interest in human-robotic co-manipulation of objects. While the human operator provides the intelligence, the robotic device provides additional force to support the human.

A diversity of related solutions has appeared. One trend among these was and still is the development of so-called exoskeletons. These resemble a mechanical suit worn by the human operator. If worn, the exoskeleton can provide additional force that allows the human to carry heavier loads. Besides the exoskeleton solutions, which are in direct contact with the human, there are also other kind of solutions available. These solutions use a separate robotic device which is not per se in direct contact with the human operator. The applied control strategies ensure additional force provided by the robotic device.

However, not all of these control strategies cover joint load co-manipulation where the robotic device should amplify the human operator’s force. Key issues with such mutual load co-manipulation is that the masses and sizes of different loads can fluctuate significantly and are unknown beforehand (e.g. suitcases, patients, building materials etc.). Furthermore the human force acts directly upon the load. Therefore the robot does not have any direct coupling with the human operator besides via the load.

Some of the proposed control strategies use variations of compliant motion control to let the operator experience certain impedance characteristics that simplify the task to be performed [2, 4, 3, 22, 29, 24, 20]. Other control strategies really amplify the applied human operator forces.
1.3. CONTRIBUTION OF THE THESIS

However, both make use of force sensors to measure the human force. Here, the fact that the human force acts directly upon the load itself, hinders the use of a force sensor to measure the human force applied. Besides that the placement of such sensor on the load is often impossible, it is also regarded as highly undesirable due to several drawbacks such as for example additional costs or vulnerability to impact. Other existing control strategies offer support by amplification of a human operator force estimate [48, 19, 36, 18, 39, 38, 17, 47, 35, 37, 42, 44, 27, 28, 1, 49, 11, 50]. However, all of these disqualify for the purpose of this thesis because they are not able to cope with the additional unknown dynamics which are introduced by the variation in loads.

All these control strategies will be discussed more extensively in a literature review following in the next chapter. For this thesis the following problem statement is formulated:

*Design and develop a force-sensorless control strategy that can provide scaled human power assistance by means of a robotic device, while carrying unknown loads.*

1.3 Contribution of the thesis

To the author’s best knowledge there is only one solution readily available complying with this problem statement. This existing solution has originated from other research performed at the Eindhoven University of Technology [41]. This research was also performed in the framework of the Teleman project. Their proposed controller will also be introduced and discussed in this thesis. Its developments are just in their early stages and some problems are yet to be overcome. Therefore, the development of inherently different approaches to solve the same problem is deemed important and can offer new future perspectives. While their approach is based on a robust controller, this thesis proposes a controller of the adaptive type. Both will be introduced in Chapter 3.

The contribution of this thesis is twofold. The main emphasis is on the development of a newly proposed controller that solves the problem at hand. The functionality of the proposed controller is analyzed and weaknesses and strengths are discussed. This is done by simulations and implementation on a real experimental setup.

Besides the design and development of a new controller, the already existing controller solution will also be analyzed by means of simulation and experimental implementation. Then a comparison between the two different strategies will be made to highlight their advantages or disadvantages compared to each other.

1.4 Outline of the thesis

The complete contribution of this thesis is distributed over the subsequent chapters as follows.

In Chapter 2, a detailed literature review on human-robotic co-manipulation and external force observers used for amplification purposes is given. The related work is discussed and it is elaborated why none of these provide a solution for the problem statement of this thesis. The chapter ends with a reflection on how the two controller solutions presented in this thesis inherently differ and why they, contrary to the others, are able to offer a solution to the problem statement.

At the beginning of Chapter 3, the problem statement is presented in more detail by introducing exact requirements and assumptions. In the sections that follow both controller solutions are introduced in more detail.
In Chapter 4, both controllers are put to the test by means of simulations. First an ideal case is considered to show their basic functionality. This is followed by two other cases to study the effect of circumstances encountered in real robotic setups. The two additional simulation cases cover the effect of friction and quantized measurement signals, respectively, which both may significantly affect the performance. In all cases the controllers are first discussed on their own merits. A discussion on the comparison of the two solutions follows next.

After having introduced the design of both controllers and analyzed their behavior by means of simulation, the step that remains is the validation by experimental implementation on a real robotic setup. These experiments will be performed by using a CFT-transposer robot as introduced in Chapter 5. Experimental results will be shown and discussed so that they can act as a proof of concept for both controllers. Results of both controllers will also be compared on an experimental level.

In the final chapter, Chapter 6, conclusions are drawn with respect to all results and discussions in the prior chapters. These conclusions are followed by recommendations for possible improvements and future research.
Chapter 2

Literature review

2.1 Introduction

As discussed in the previous chapter, it is not likely that robots will perform load transportation fully autonomously in the near future. Therefore, an intermediate step will be the inclusion of a human operator in the control loop, which is providing the required intelligence. In the previous chapter the following problem statement is defined: design and develop a force-sensorless control strategy that can provide scaled human power assistance by means of a robotic device, while carrying unknown loads.

This is a specific form of human-robotic co-manipulation of objects. Therefore, in Section 2.2 first attention is being paid to existing literature on the different kind of approaches towards human-robotic co-manipulation. A discussion shows why none of these existing approaches provide a solution for the problem statement of this thesis.

Furthermore, for the problem statement, it is of special interest to estimate the human operator’s force which is applied directly upon the load. Therefore, Section 2.3 presents an extensive overview of solutions that already exist to estimate an external force applied on a robotic manipulator. It will make clear why none of these provides a solution for the stated problem.

Finally in Section 2.4, the existing controller that followed from other research within the Teleman project and the proposed controller approach from this thesis will be briefly introduced and discussed. Here the emphasis is on how they differ from already existing results and each other. Furthermore it is discussed why these approaches, in contrary to those other approaches, may provide a suitable solution.

2.2 Review on human-robotic co-manipulation

Throughout the literature there appears to be great interest in all kind of interaction of robots with humans. The problem as discussed in this thesis focusses on human-robotic co-manipulation of loads.

The idea of using a robotic device to support a human is not new. Already in 1989 Kazerooni introduced some concepts regarding this matter [16]. He envisioned robots in direct physical contact with a human. Therefore he appoints the name 'extenders' to this kind of robotic support. The human and robot should collaborate by exchanging information and power signals with each other.
2.2. REVIEW ON HUMAN-ROBOTIC CO-MANIPULATION

Nowadays several works are published investigating human-robotic co-manipulation of loads. Some clearly focus on how the interaction between the human and the robot should be established when collaborating [7, 8]. Researched subjects are for example what part vision or oral communication can play in achieving such collaboration. Also, how humans intuitively react in collaboration with a robot. However, the approach of this thesis is not really related. This thesis focusses more on the issue of real force support by scaling the human power.

In [26] a robot named "Mr. Helper" is developed for the purpose of handling an object in cooperation with a human. For lifting-up/down of the load a control scheme is suggested that ensures that the robot wrist angles, generated by the operator’s lifting-up/down motion, converge to zero. This is applicable to stretched objects where the robot and the human each carry at opposite sides. Furthermore, "Mr. Helper" is equipped with six-axis force/torque sensors attached at the wrists. These measure the human’s intentional force. A control scheme ensures that the robot handles the load such that the human experiences a certain impedance when moving the load. In [25] a new controller approach is developed for trajectory tracking of "Mr. Helper" while collaboratively transporting a load. Here the intentional force of the human operator is again measured by the wrist sensors. While moving along a certain trajectory, the suggested controller should ensure that a mobile base, which carries the manipulators, follows the same trajectory as the carried moving object has done. This is valuable to avoid obstacles as a normal human carrying would do.

In [45] and [46] they have some improved variations to this concept. Improvements follow from using a stereo vision to guide the robot and to decouple influences between the mobile base and the upper robot part carrying the load. Both aim again at avoiding obstacles when cooperatively transporting loads. Clearly, these do not offer a solution for scaling the human force as desired.

In [2, 4] variations of compliant control schemes are introduced. A force sensor is attached to the robot’s wrist. By using this force sensor measurements, the robot is controlled to follow the motion selected by the human operator. The compliant motion control introduces a force feedback to let the human operator experience certain desired impedance characteristics.

In [3] a dual controller consisting of a Lower Reflex Control loop and an Upper Reflex Control loop is proposed. The lower reflexive action is to move the end-effector using a compliant motion control. Again, a force sensor attached to the robot’s wrist is used for providing force information. The Upper Reflexive Controller, providing a supervisory control loop, regards human operator corrections as impulsive forces. If so, which is the case if the manipulator itself acts as a load on the human arm, these upper control loop adds an additional force input to the lower compliant motion control to affect the controller behavior as desired. This improves the speed of the manipulator in response to the motion of the human arm. In a way the controller anticipates the movement of the arm and applies the required corrections in advance.

Encouraged by these results some researchers of the previous works continued to work on this problem. In [21] a model predictive control law to cope with the load sharing problem is proposed. Based on force sensor information the desired movement initiated by the human arm is predicted. An estimated trajectory is also determined. In a defined cost function the error between the future desired and estimated trajectories is minimized, utilizing the available information at the present time. Therefore the effort necessary to handle the loads is minimized. However, only simulated results are shown and the scaling of the human force is not subject to a certain tunable factor as desired in this thesis.

Instead of estimating the desired trajectory, [22] uses a memory with several skillful trajectories stored in it. When the robot finds a matching trajectory it travels along this trajectory without human assistance required. When the human operator notices that the path of the object is not, or will not be, acceptable, he interrupts the motion and applies compliant control. This com-
pliant control scheme uses force information measured by a force sensor attached at the robot’s wrist. If load transportation is a process with certain repeated patterns this could be a solution for human-robot co-manipulation of loads. However, it does not offer a solution for human-robot co-manipulation of loads for random trajectories where the human requires scaled force support.

Using measured force information that follows from a sensor attached to the wrist of the robotic manipulator is quite common. In [24] it is done to obtain force information used in a control loop. This controller ensures that the human operator can manipulate or position the load with defined impedance characteristics while being helped by two robot manipulators. Another variable impedance control scheme can be found in [20]. Also [29] applies a virtual compliant control scheme to implement defined impedance characteristics. However, they integrate a real-time estimation of the human motion for the human-robot cooperative manipulation.

A power assisting controller is proposed in [13]. The proposed method is based on dividing the unknown load into a gravitational component and a dynamic component. Each component is compensated by an individual ratio. Therefore two force sensors are installed, one to measure and amplify the human operator’s force and one to measure the forces introduced by the unknown load itself.

Another variation is found in [5]. A method is proposed in which a human and a robot support each end of a long object and manipulate it cooperatively in a horizontal plane. The robot is given a virtual nonholonomic constraint equivalent to a wheel attached to the object in the axial direction. The constraint and controlled cooperation is achieved using anisotropic impedance control in the end-effector frame. The impedance control is again based on force sensor information.

In [14] first a relation between the human behavior and the desired angular velocity is experimentally established. Based on this relation the desired angular velocities are estimated from force sensor information and joint angular information. These desired angular velocities are used to control the manipulator in the vertical plane. In the horizontal plane a common impedance controller based on the force sensor measurements is implemented.

Note that all of the previous approaches for human-robotic co-manipulation of loads make use of a force sensor installed at the end-effector. In all cases the force sensor provides a measured quantity of the human operator’s force. However, in the problem statement of this thesis it is explicitly noted that the controller strategy providing power assistance should act in a force-sensorless fashion. The use of force sensors is known to be subject to several drawbacks [1, 34]: examples are additional costs, mounting issues (e.g. installation space etc.), noisy data, changing manipulator’s dynamics and a dead band on initial contact. Furthermore their fragility is an issue. The installed force sensor should be robust enough to survive repeated impacts and abrasions but unfortunately they appear to be not very durable and vulnerable to impact. Finally there are some environmental issues when using force sensors such as temperature influences or high (water) pressures. For an extensive overview of force sensor related issues the reader is referred to [34].

These mentioned disadvantages limit the use of force sensors. Some, such as for example costs, mounting and fragility, clearly also apply to the kind of objective considered in this thesis. More work can be found in literature that acknowledges these force sensor drawbacks. These works indicate the need for force-sensorless approaches to identify external forces. In the next section, several approaches for estimating external forces in a force-sensorless manner will be discussed.
2.3 Review on external force estimation

For many control applications, knowledge on the external forces is of interest. In some cases the external force is regarded as an undesired disturbance and needs to be canceled. In others, similar to the thesis’ objective, the external force is of interest for amplification purposes. Either way, the external force applied needs to be measured or estimated. As shown in the previous section, obtaining external force estimates in a force-sensorless manner has preference or may even be the only option. Therefore several alternatives to estimate the external forces acting on the end-effector of a robot have been developed and are briefly discussed next.

K. Ohnishi and different co-authors have published several papers regarding force estimation by using observers \[48, 19, 36, 18, 39, 38, 17, 47\]. All these papers use the same robust force observer. The fundamental idea is that the system can be described as a single-mass model with a nominal inertia matrix. All deviations from this model are observed and regarded as disturbances. These disturbances are due to external forces acting on the system or resulting from internal sources such as model errors, centrifugal and Coriolis forces, gravitational forces and friction forces. These internal sources are assumed to be known after an experimental identification of the system. Then it is easily noticed that the external forces can be determined as the rest of the total disturbances after subtracting the sum of forces following from all the internal sources. The proposed force observer is implemented in an experimental setup and shows quite reasonable results. However, a critical issue remains. Perfect model knowledge is assumed after experimental identification. In the problem statement as defined in Section 1.2, an unknown load is present which will introduces additional uncertainty. Therefore the experimental identification will not cover all forces following from the internal dynamics, which will result in a wrong estimate of the external force.

In \[35\] an extended version of the previously described observer is discussed. It is extended by using information from an acceleration sensor. Due to a higher bandwidth of the observer, improved estimation results are obtained. However, despite the increased bandwidth and the improved result, the important drawback mentioned earlier remains.

The same observer as proposed by K. Ohnishi and co-authors is also used in \[37\]. Here an exactly identical twin robot system is used. It is assumed that friction, system parameters etcetera are exactly identical for both robots. One robot experiences the external forces that need to be estimated, while the other one always moves in a synchronized manner in free space. Then it is easily noticed that the difference in the observed disturbance is only due to the external forces being applied. Good experimental results are shown. However, the obvious significant disadvantage of this solution of external force estimation, is the need of an extra exactly equal robot system. It will be obvious that this method can not be regarded as a solution for the problem under study here because of the need of a twin robot system. What worsens things is that the twin robot system should also carry an equal unknown load to make the method still work properly for the problem setting of this thesis.

Slightly different solutions by using linear observers are discussed in \[42\]. Special attention is being paid to the usage of an inner loop disturbance observer in combination with an outer loop external force observer. The inner loop should suppress disturbances due to internal sources, i.e. model deviations. This improves model matching. If done correctly then the external loop estimates the disturbance that is solely due to the external forces. Again both observers are based on a nominal model and therefore modeling errors or unknown dynamics will directly affect the estimation accuracy of the external force. Also bandwidth limitations are imposed. In this work the power assisting analyses are based on creating certain defined impedance characteristics. If
power assistance with a defined amplification factor of the external force is required, then some adaptations should be made. However, it still will not be able to handle the unknown loads.

Besides the linear observer solutions described above, several nonlinear solutions to estimate the external force are presented in literature. Most of them use the well-known equations of motion describing the robotic manipulator [44]. The system input force is estimated by using a model that incorporates the equations of motion. The model input consists of state feedback information. Furthermore the real controlled input force is known. Therefore, the external force is easily estimated by subtracting the real controlled input force from the estimated input force that follows from the model. The model parameters are experimentally identified. Again modeling errors or unknown dynamics will directly influence the estimation accuracy.

Variations to such a common nonlinear solution can be found, for example in [27]. Here the problem of inaccurate modeling is avoided by first using a linear disturbance observer that cancels all the disturbances that follow from deviations from a defined linear nominal model. During an initial adaptation phase without external forces acting on the system, a disturbance observer output estimator is adapted to correctly estimate the canceled disturbance. After adaptation has finished, an external force can be applied. Then the difference between the canceled disturbance following from the disturbance observer and the estimated disturbance following from the disturbance observer output estimator gives an estimate of the external force acting on the system. Again an obvious disadvantage is the initial learning period to adapt the disturbance observer output estimator. This adaptation period should occur for every new load attached to the end effector of the manipulator.

In order to cope with inaccurate experimental parameter identification, [28] also introduces an adaptation algorithm applied during an initial learning period without external forces present. After this learning period the identified model is assumed to give a good estimate of the system dynamics. Then, the difference between control input force and estimated system input force following from the identified model, gives the estimated external force. Experimental results show that using an adaptation law to improve the model parameter estimates is an improvement over the need of a full identification procedure. However, the paper claims to easily cope with changing dynamics. But the estimate can only be adapted if no external force is applied and in the experimental results shown this adaptation period even takes an unpractical time of ten minutes. Again the need for an adaptation period for each different load before estimation can occur, prevents this approach from providing a solution to the problem addressed in this thesis.

The nonlinear observers mentioned above assume exact model knowledge in combination with experimental parameter identification or an adaptation law with a learning period to adapt the parameters. Another procedure that gives an estimate for the external force and avoids the influence of dynamic modeling errors is using neural networks [1, 49, 11]. Advantages of using neural networks is that they do not require any dynamic model knowledge at all, no requirements on the persistence of excitation and no need for linearity in the unknown system parameters and the need for tedious computation of a regression matrix [50]. The neural network typically undergoes a training period before it can be used for estimation. In [11] the external force directly follows from the trained neural network but still a force sensor is needed during the training period.

A major disadvantage of using neural networks is that the solution of finding the best neural network structure has no general solution. Finding a proper network structure is a matter of trial-and-error. Despite this disadvantage, [1] shows an improvement of estimating the external force with 40% if acceleration information is used to train the network and without acceleration information an improvement of 20% compared to the model-based approaches. Besides the
disadvantage of finding a proper neural network structure, again the initial training period needed remains an obstacle to fulfill the research objective as presented before, because, for each different load carried, performing a new training period is a necessity.

Unfortunately, all the force estimation approaches described above assume either perfect model knowledge by experimental parameter identification or an initial adapting/training period. While using these solutions, the dynamics may not change anymore to properly estimate the external force. Both experimental parameter identification or training periods are not an option for the problem discussed here. Identifying dynamic parameters is not possible because different loads vary and thus so does the additional dynamics introduced by the load. For the same reason for each newly carried load a relearning adaptation period should be introduced which obviously is also not an option. For all these solutions it holds that if the model used is incorrect, the estimated external force will also be incorrect. Therefore, providing correct force-sensorless power-assistance in a human-robotic co-manipulation setup to transport various heavy loads, where the end-effector is guided by the force applied by the human operator, is not possible with one of these solutions.

In the next section the existing controller approach that followed from other research within the Teleman project and the basic ideas behind the proposed controller approach from this thesis will be briefly introduced and discussed.

2.4 Discussion in perspective of current research

As already mentioned in Chapter 1, the Teleman project already proposed a robust controller solution to the problem. It pseudo-linearizes the system by providing force feedback that follows from a model-based controller. This model-based controller uses identified dynamic parameters of the assisting robotic manipulator but not of the load. If this controller acts properly, and thus compensates accordingly for the dynamics of the links of the robot without the load, only the dynamics of the carried unknown load remain. Another part of the controller, actually providing the power assistance, acts in a cyclic manner consisting of two phases. In the first phase it estimates the human force by applying a linear negative feedback. This negative feedback loop results in a system output to correctly settle at the value of the applied human operator's force. Thus after settling an estimate of the human operator's force is available. In the second phase, a scaled version of the human operator's force estimate is applied to the load. This solution is robust for large variations in the unknown loads provided that the mass of the load is within certain bounds.

To the best knowledge of the author there are, besides the previous one, no solutions available for the problem as presented here. The developments of the currently proposed controller approach are just in their early stages and continue to progress. However, some problems are yet to overcome. So far, the performed research is restricted to regarding the load as a point mass, so excluding moments of inertia acting in the case of real loads. Also handling gravity needs some additional attention. Therefore, the development of alternative and inherently different approaches to solve the problem statement is an interesting option. Inherently different approaches will offer new perspectives with probably other advantages and/or disadvantages. Examples of possible differences in control approaches that could appear to be interesting, i.e. be an advantage, are: feedback estimates dependency, no a priori knowledge about the possible load masses required, possible adaptations to cope with time varying loads, possibilities to cope with moments of inertia etc. Whether such advantages are indeed the case for each specific controller
should become clear in the simulation studies of Chapter 4 and the experiments of Chapter 5.

Next, the newly proposed controller is briefly introduced. This will clarify the inherent difference between the two controller approaches. While the existing approach is based on a controller robust for a bounded range of load masses, this thesis proposes a controller of the adaptive type. The proposed Power Assisting Controller is based on a new cyclic adaptive-acceleration concept. The controller should, contrary to the solutions of the previous sections, be able to estimate and scale the applied human force while unknown loads are carried in a force-sensorless manner. Similar to the existing controller solution, the solution of this thesis also acts in cycles consisting of two separate phases. In the first phase the controller determines the human operator's intention by observing the acceleration of the load. In the subsequent phase the controller simultaneously adapts an estimate of the mass of the unknown load, while also directly providing an additional scaled force estimate to enhance the human's performance.

By giving these short introductions of both controllers, it might be clear to the reader how these solutions essentially differ from the solutions provided in the literature as discussed in the previous section. Namely, both approaches eliminate the dependence on a model incorporating the dynamics of the unknown load. The essential key here is acting in a cyclic manner. This division in two different phases provides a way of circumventing the problem with the unknown load dynamics. In the following chapter both controller solutions will be presented and discussed in full detail.
Chapter 3

Control design for human-robotic co-manipulation

3.1 Introduction

In Section 2.2 and Section 2.3 of the previous chapter, several control approaches are reviewed for human-robotic co-manipulation or external force estimation, respectively. Some works also aim at providing power assistance. However, both sections showed that none of the presented approaches offers a solution to the problem studied in this thesis.

In Section 2.4, however, the basic idea of another work that does provide a solution is already introduced. This solution is readily available but developments are just in their early stages. Therefore this thesis proposes an inherently different control approach. One of the contributions of this thesis will be the comparison of both controllers. By doing so the reader can obtain more insight in the weaknesses and strengths related to each controller solution. To be able to compare, this chapter will describe the design of the existing controller as well as the design of the newly proposed controller approach of this thesis.

First the detailed problem statement including requirements and assumptions is introduced in Section 3.2. Hereafter Section 3.3 will first introduce the existing controller solution in Section 3.3.1. This is followed by Section 3.3.2 which will describe the newly proposed Power Assisting Controller in detail. The chapter concludes with a first comparison of both controller approaches in Section 3.4.

3.2 Problem statement including requirements and assumptions

The main objective of this research is the design and development of a new Power Assisting Controller (PAC). A human operator applies a force directly acting on the load carried by the robotic manipulator. The Power Assisting Controller should, by means of the robotic manipulator, provide a scaled amplification of this force. The human will still provide direct guidance to the movement/positioning of the load, but because of the power assistance provided the human will feel a load with lower mass, i.e. the human needs to apply less force to realise certain desired trajectories. The human operator will be able to handle heavier loads or faster transportation using the Power Assisting Controller. When designing a Power Assisting Controller that can perform this task, two issues are encountered:
• The force that the human operator applies to the load can not be measured, i.e. the designed controller should function in a force-sensorless fashion;

• The mass $m$ of the load is unknown but is bounded according to $m \in [m_{\text{min}}, m_{\text{max}}]$.

Furthermore the following assumptions are made:

• The load can be regarded as a time-invariant point-mass. So moments of inertia and supplementary dynamics are neglected;

• For this initial study gravity is neglected;

• Only position measurements of the robot links are available;

• Only load movement in one degree of freedom is considered thus far.

The problem setting as considered in this thesis is schematically depicted in Figure 3.1. Here $H$ represents the human operator that applies a certain control strategy to follow a desired trajectory $x_d$. Note that the human operator, providing guidance by applying a force $F_H$ to the load, acts as a human-in-the-loop controller. Hereby the visual feedback of the current Cartesian position $x$ of the load is available to the human operator. So the human operator is solely responsible for the path planning and corresponding position control.

The block $FK$ represents a forward kinematics block to transform the measured joint coordinates $q$ to Cartesian coordinates $x$. The load is represented together with the assisting robotic device as one system in the block $RL$. The Power Assisting Controller is represented in the block $PAC$. It should estimate the human force (with the estimated indicated by $\hat{F}_H$) and provide assistance by adding an input $u = \alpha \hat{F}_H$ to the system. Here $\alpha > 0$ represents the scaling factor of provided power assistance.

3.3 Controller design

The emphasis of this report is on the development of a newly proposed power assisting controller. However, as mentioned before in the previous chapters, [41] already proposed a controller to serve this purpose. The report will refer to this type of power assisting control as Negative Feedback Estimation (NFE) Controller due to the inherent nature of human force estimation by applying negative feedback in the first phase. Else, if not explicitly noted, with Power Assisting Controller (PAC) the report refers to the controller developed in the current work.
In order to explain the basic idea behind the design of both controllers, a simple system model is used. In this initial study only one degree of freedom is considered. Therefore a simple system model including a one degree of freedom mass model is used:

\[ F_H(t) + u = m\ddot{x}, \]

(3.1)

where \( u \) is the controller’s output, \( F_H(t) \) the human operator’s force, \( m \) the moving unknown mass and \( \ddot{x} \) the acceleration.

### 3.3.1 Design Negative Feedback Estimation Controller

Note that, contrary to the original paper [41], in this study only one degree of freedom is considered and therefore the model as defined in equation (3.1) is used. For an extended description of the control design for the multiple-degree-of-freedom case the reader is referred to the paper.

The challenge that one faces when designing such a power assisting controller is the fact that there are two unknowns, the mass of the load and the human operator force and only one equation, namely (3.1). Therefore, the NFE controller proposes to tackle this problem in a repetitive cyclic fashion, containing two temporal steps:

1. Estimate the human operator force;
2. Apply the scaled force.

These steps are performed in two separate phases that together form one algorithm cycle as shown in Figure 3.2. Next, these two phases will be discussed in more detail.

![Figure 3.2: Full algorithm cycle, showing the two separate phases.](image)

#### Estimation phase

The following definition is introduced:

\[ \eta^{(p)} := \ddot{x}, \]

(3.2)

with \( p \geq 1 \) a constant integer and \( \eta^{(p)} \) denoting the \( p^{th} \) time-derivative of \( \eta \) (i.e. \( \eta = \int^p \ddot{x}dt^p \)). Then the model of (3.1) is equivalent to:

\[ m\eta^{(p)} = u + F_H(t). \]

(3.3)
3.3. CONTROLLER DESIGN

Note in Figure 3.2 that the controller strategy provides negative feedback during the estimation phase defined as:

\[ u = - \sum_{i=0}^{p} K_i \eta^{(i)}, \]  

(3.4)

where \( K_i, i = 0, \ldots, p \) are feedback gains. The considered output of the system is the estimated human force as:

\[ \hat{F}_H(t) = K_0 \eta. \]  

(3.5)

To prove that the estimated force converges to the real human force, i.e.:

\[ \lim_{t \to \infty} (F_H(t) - \hat{F}_H(t)) = 0, \]  

(3.6)

the dynamics of the obtained closed-loop system (3.3), (3.4) and (3.5) are transformed to the Laplace domain which gives:

\[ m s^2 \eta(s) = -(K_0 + K_1 s + \cdots + K_p s^p) \eta(s) + F_H(s), \]  

(3.7)

\[ \hat{F}_H(s) = K_0 \eta(s), \]  

(3.8)

where \( s \in \mathbb{C} \) is the Laplace variable, \( F_H(s) = \mathcal{L}(F_H(t)), \hat{F}_H(s) = \mathcal{L}(\hat{F}_H(t)), \eta(s) = \mathcal{L}(\eta) \) and \( \mathcal{L}(\cdot) \) is the Laplace operator. Then the transfer function from the human operator input \( F_H(t) \) to the estimating output \( \hat{F}_H(t) \) is given by:

\[ H(s) = \frac{\hat{F}_H(s)}{F_H(s)} = \frac{K_0}{(m + K_p) s^p + K_{p-1} s^{p-1} + \cdots + K_0}. \]  

(3.9)

If the parameters \( K_i \) are chosen such that, independently of \( m \) (where \( m \in [m_{\min}, m_{\max}] \)), it is guaranteed that the polynomial denominator of (3.9) is Hurwitz, then the estimation problem is solved for constant human forces \( F_H(t) \) since:

\[ \lim_{s \to 0} H(s) = 1, \]  

(3.10)

which implies that equation (3.6) holds. This can be shown as follows. The relation between equation (3.6) and (3.10) is based on the Final Value Theorem [12] that implies that for a stable system \( G(s) \), where \( G(s) = \mathcal{L}(g(t)) \), holds:

\[ \lim_{t \to \infty} g(t) = \lim_{s \to 0} s G(s). \]  

(3.11)

If \( F_H(t) \) is constant it can be regarded as a unitary-step input for which the Laplace transform is given as \( \frac{1}{s} \). Assuming such an unitary-step input in combination with equation (3.11) gives the final value of the system after all transients have decayed as:

\[ \lim_{s \to 0} s G(s) \frac{1}{s} = \lim_{s \to 0} G(s), \]  

(3.12)

and thus:

\[ \lim_{t \to \infty} g(t) = \lim_{s \to 0} G(s), \]  

(3.13)

holds for constant inputs. This clarifies how (3.6) follows from (3.10) under the conditions that \( H(s) \) is a stable system and \( F_H(t) \) can be regarded constant, because \( \lim_{s \to 0} H(s) = \frac{\hat{F}_H(s)}{F_H(s)} = 1 \)
3.3. CONTROLLER DESIGN

which under these conditions, according to (3.13), therefore implies that for the time-domain
\[
\lim_{t \to \infty} (F_H(t) - \hat{F}_H(t)) = 0.
\]

Besides choosing the parameters \( K_i \) to ensure the polynomial denominator of \( H(s) \) being
Hurwitz, they also affect the estimation algorithm’s bandwidth. The choice of the parameter \( p \)
and the gains \( K_i \) should be done such that \( |H(j \omega)| \approx 1 \) up to a frequency above the typical
frequencies in the human force signal \( F_H(t) \). Furthermore the settling time should be lower
than the time \( T_1 \) (see Figure 3.2) to ensure an accurate estimate is available before the end of the
estimation phase. This requirement should also be satisfied for the complete range of masses,
\( m \in [m_{\text{min}}, m_{\text{max}}] \).

Amplification phase

For the second phase of the algorithm an estimate \( \hat{F}_H(t) \) is now available to be amplified. Note
that the problem statement requires the added force to be equal to \( \alpha F_H(t) \) over the complete
cycle. In the first estimation phase, however, a negative feedback is applied. Therefore a new gain
\( \beta \) to amplify \( \hat{F}_H(t) \) has to be determined to still meet this requirement of an overall amplification
of \( \alpha F_H(t) \).

If the algorithm cycles execute at a considerably high frequency (\( \geq 100 \text{Hz} \)), then the hu-
man force \( F_H(t) \) can be considered to be approximately constant during one cycle, i.e. \( F_H(t) \approx
F_H(kT_a) \) \( \forall t \in [kT_a, (k + 1)T_a] \) where \( T_a \) is the duration of one cycle, see Figure 3.2. This is
required to let the proof that equation (3.6) holds still be valid according to the Final Value The-
onrem, which will be shown in Subsection 3.3.3. Under this assumption the human applies the
force \( F_H(kT_a) \) and the robot should apply the average force \( \alpha F_H(kT_a) \) during the length \( T_a \) of the
\( k \)th cycle. The controller, and therefore the robot, applies a force input as:

\[
u(t) = -\sum_{i=0}^{p} K_i \eta^{(i)}, \quad \forall t \in [kT_a, kT_a + T_1],
\]  
(3.14)

\[
u(t) = \beta \hat{F}_H(kT_a + T_1), \quad \forall t \in [kT_a + T_1, (k + 1)T_a].
\]  
(3.15)

If the bandwidth of the estimation algorithm is chosen high enough, and therefore the estimation
algorithm has a small settling time, the input during the estimation phase is approximately equal to:

\[
u(t) = -\hat{F}_H, \quad \forall t \in [kT_a, kT_a + T_1],
\]  
(3.16)

instead of equation (3.14). If furthermore it is assumed that \( F_H(t) \approx \hat{F}_H(t) \), i.e. the estimation is
working, then the equation from which the desired \( \beta \) can be obtained becomes:

\[
\alpha F_H(kT_a) = \frac{1}{T_a} (\beta(T_a - T_1)F_H(kT_a) - T_1 F_H(kT_a)),
\]  
(3.17)

where it is used that the average applied force over one cycle (\( kT_a \leq t < (k + 1)T_a \) should equal \( \alpha F_H(kT_a) \). And thus the desired \( \beta \) is easily solved to be:

\[
\beta = \frac{\alpha T_a + T_1}{T_a - T_1}.
\]  
(3.18)
3.3. CONTROLLER DESIGN

3.3.2 Design Power Assisting Controller

Because the problem statement is the same for both controllers, so are the challenges to be faced. Also the proposed Power Assisting Controller has to cope with the issue that there are two unknowns, the mass of the load and the human operator force and only one equation. Similar to the NFE controller, the Power Assisting Controller deals with this in a cyclic fashion that consists of two separate phases. The control steps performed in the two phases consist of:

1. Quantifying the human operator’s intention by means of acceleration estimation; the acceleration estimate has a direct relation with the human operator’s force.

2. Estimate the mass of the load by adaptation and simultaneously apply a scaled human force estimate.

Together these performed steps form one algorithm cycle as shown in Figure 3.3.

![Figure 3.3: Full algorithm cycle, showing the two separate phases.](image)

This directly reveals the essential difference in both approaches. While the NFE controller is a robust control for an uncertain mass \( m \), the PAC applies an adaptation algorithm in the second phase to obtain an accurate estimate \( \hat{m} \) for the mass \( m \). A more thorough discussion about these differences in controller approaches follows in Section 3.4. First, the two phases of the PAC controller are studied in more detail.

Estimation phase

![Figure 3.4: System in phase 1.](image)

During this phase the acceleration of the load induced by the human operator upon the load is estimated. Therefore the added controller output is set to zero, i.e. \( u = 0 \) (see Figure 3.4). Then (3.1) becomes:

\[
F_H(t) = m\ddot{x} \quad \Rightarrow \quad \ddot{x} = \frac{F_H(t)}{m}.
\]  (3.19)
Thus by doing so, a direct relationship between the human input $F_H(t)$ and the present acceleration originates. Therefore the current acceleration can be used to represent the human input. By definition:

$$\ddot{x}_H := \frac{F_H(t)}{m}, \quad (3.20)$$

which denotes the acceleration solely due to the human input. Obviously it then follows that during the estimation phase it holds that:

$$\ddot{x}_H = \ddot{x}. \quad (3.21)$$

Note that $\ddot{x}$ is not directly available since only position $x$ is measured according to the problem statement. Therefore a suitable double differentiation algorithm should be applied to the measurements, to obtain an acceleration estimate $\hat{\dot{x}}$. And thus also $\ddot{x}_H$ follows in this first estimation phase directly from this acceleration estimate and should therefore be denoted as $\ddot{x}_H(\equiv \hat{\dot{x}}$ in the estimation phase). For both phases it differs how $\hat{\ddot{x}}_H$ is obtained as will be explained next.

In the subsequent enhancement phase the estimate $\hat{\ddot{x}}_H$ is used to represent the human’s intention to accelerate the load. However if the control input $u \neq 0$, which is the case in the adaptation/enhancement phase, then equation (3.21) does no longer hold. Therefore data samples of $\hat{\ddot{x}}_H$ are stored during the estimation phase. These stored data samples in combination with a suitable choice of an extrapolation function provide the estimate $\hat{\ddot{x}}_H$ for the acceleration induced by the human in the subsequent enhancement phase.

If the algorithm executes with a frequency much higher than the human force signal, then it is assumed that $F_H(t)$ and therefore $\ddot{x}_H$ are constant during one algorithm cycle. Therefore:

$$\ddot{x}_H(t) = \ddot{x}_H(kT_a), \quad \forall t \in [kT_a, (k+1)T_a], \quad (3.22)$$

Consequently, a suitable choice of an extrapolation function to provide $\hat{\ddot{x}}_H$ in the subsequent enhancement phase is a zero-order-hold function applied to the last sample $\hat{\ddot{x}}_H$ of the first phase. Thus while $\hat{\ddot{x}}_H$ in the estimation phase is directly obtained as:

$$\hat{\ddot{x}}_H(t) = \hat{\ddot{x}}, \quad \forall t \in [kT_a, kT_a + T_1], \quad (3.23)$$

it is provided in the second phase as an extrapolated constant:

$$\hat{\ddot{x}}_H(t) = \hat{\ddot{x}}_H(kT_a + T_1), \quad \forall t \in [kT_a + T_1, (k+1)T_a]. \quad (3.24)$$

With a good estimate of $\ddot{x}_H$ now available as $\hat{\ddot{x}}_H$ for both phases, which is solely dependent on the human operator’s force according to (3.20), the human operator’s force estimate is easily calculated if a good mass estimate $\hat{m}$ is available as:

$$\hat{F}_H(t) = \hat{m}\ddot{x}_H, \quad \forall t \in [kT_a, (k+1)T_a]. \quad (3.25)$$

However, such a good mass estimate $\hat{m}$ must first be obtained. This is done by applying an adaptation law in the second phase as will be explained next.
Adaptation / enhancement phase

Similar to the NFE controller, a gain $\beta$ has to be determined for amplification of the human force in the second phase. Again this gain $\beta$ should ensure an additional overall force of $\alpha F_H(t)$ provided by the controller (see Figure 3.5).

If the algorithm cycles execute at a considerably high frequency ($\geq 100Hz$), then the human force $F_H(t)$ can be considered constant during one cycle:

$$F_H(t) = F_H(kT_a), \quad \forall t \in [kT_a, (k+1)T_a],$$  \hspace{1cm} (3.26)

where $T_a$ is the duration of one cycle, see Figure 3.3. Under this assumption the human applies the force $F_H(kT_a)$ and the robot should apply an average force of $\alpha F_H(kT_a)$ over the $k^{th}$ algorithm cycle. The Power Assisting Controller applies a force input as:

$$u(t) = 0, \quad \forall t \in [kT_a, kT_a + T_1],$$  \hspace{1cm} (3.27)

$$u(t) = \beta \dot{F}_H(t), \quad \forall t \in [kT_a + T_1, (k+1)T_a].$$  \hspace{1cm} (3.28)

It must be noted that in this second phase the mass estimate $\hat{m}$ is estimated by adaptation. How this adaptation functions is explained further on. However, it is important to note that in the first few cycles it is not guaranteed that $\hat{F}_H(t) \approx F_H(t)$. This is due to the fact that the mass estimate might not have converged yet to approximately the real value $m$. The speed of this desired convergence and therefore the number of cycles necessary before $\hat{F}_H(t) \approx F_H(t)$, depends on a tunable controller gain and the initial estimate of $m$ as will be clarified later on. The $\beta$ calculated here is valid after the estimate $\hat{m}$ has converged and it can be assumed that $\hat{F}_H(t) \approx F_H(t)$, i.e. the estimation is working. Then the equation from which the desired $\beta$ can be obtained becomes:

$$\alpha T_a F_H(kT_a) = \beta (T_a - T_1) F_H(kT_a).$$  \hspace{1cm} (3.29)

Consequently, the desired $\beta$ for this Power Assisting Controller is easily solved to equal:

$$\beta = \frac{\alpha T_a}{T_a - T_1}. $$  \hspace{1cm} (3.30)

If the desired $\beta$ is determined, the Power Assisting Controller adapts $\hat{m}$ and provides a control output $\beta \dot{F}_H(t)$ simultaneously in the second phase as will be explained next.

By substitution of the controller output in the second phase as defined in (3.28), the model (3.4) can be rewritten as:

$$\ddot{x}(t) = \frac{F_H(t) + u}{m} = \frac{F_H(t)}{m} + \frac{\beta \dot{F}_H}{m}, \quad \forall t \in [kT_a + T_1, (k+1)T_a].$$  \hspace{1cm} (3.31)

The first term of (3.31) equals the definition of (3.20). Therefore, by substitution of $F_H(t)$, (3.31) can be rewritten as:

$$\ddot{x}(t) = \frac{m \ddot{x}_H}{m} + \frac{\beta \dot{F}_H}{m}, \quad \forall t \in [kT_a + T_1, (k+1)T_a].$$  \hspace{1cm} (3.32)
3.3. CONTROLLER DESIGN

Similarly, by substitution of  \( \hat{F}_H \), which follows from (3.25), the last term of (3.32) can also be rewritten which gives:

\[
\ddot{x}(t) = \frac{m\ddot{x}_H + \beta \hat{m} \dot{x}_H}{m}, \quad \forall t \in [kT_a + T_1, (k + 1)T_a].
\] (3.33)

If the approximation of (3.26) is valid, i.e. \( F_H(t) \) can be regarded constant during one complete cycle, then (3.24) indeed gives a good estimate \( \hat{\ddot{x}}_H \) for \( \ddot{x}_H \). If the latter is assumed to be the case, i.e. the estimation phase gives a good estimate and thus \( \hat{x}_H \approx \ddot{x}_H \), then if the mass estimate \( \hat{m} \) would equal the real mass \( m \) (i.e. \( \hat{m} \approx m \)), (3.33) transforms into:

\[
\ddot{x}(t) \approx (1 + \beta) \hat{\ddot{x}}_H, \quad \forall t \in [kT_a + T_1, (k + 1)T_a].
\] (3.34)

However, initially \( \hat{m} \approx m \) is not true. The estimate of the mass, \( \hat{m} \), needs to be adapted first to ensure that \( \hat{m} \) converges to \( m \). As \( \ddot{x} \) is not directly available, the estimate \( \hat{x} \) is used instead. As long as this estimated acceleration \( \hat{x} \) during the enhancement phase does not satisfy equation (3.34), i.e. \( \hat{x} \neq (1 + \beta) \hat{\ddot{x}}_H \), then the output of the Power Assisting Controller is not correct and thus the estimate of \( m \) is incorrect and needs to be adapted correspondingly. Therefore, an adaptation law is designed as follows.

During the enhancement phase (3.34) gives a desired acceleration that, if obtained, ensures correct amplification of the actual human force \( F_H(t) \). By definition:

\[
\hat{x}_{des}(t) := (1 + \beta) \hat{x}_H, \quad \forall t \in [kT_a + T_1, (k + 1)T_a].
\] (3.35)

Then an error that represents the quality of an estimate of \( m \) can be defined as:

\[
e := \hat{x} - \hat{x}_{des}.
\] (3.36)

By using this error to adapt \( \hat{m} \) in a correct manner, the following adaptation law is designed:

\[
\dot{\hat{m}} = -\text{sign}(\hat{x}_H) \Gamma e \quad \Gamma > 0,
\] (3.37)

where \( \Gamma \) is a gain affecting the adaptation sensitivity. The total period of one complete algorithm cycle, denoted by \( T_a \), should be chosen small enough such that \( \hat{x}_H \) can be regarded constant during the enhancement phase.

Next it is shown that if the assumption of \( \ddot{x}_H \) being constant is valid and thus (3.24) gives a good estimate \( \hat{\ddot{x}}_H \), and furthermore a human force is present, it is ensured that the mass estimate \( \hat{m} \) converges to the real value \( m \).

If \( \hat{x} \approx \ddot{x} \), (3.33) can be substituted for \( \hat{x} \) in the error definition of (3.36). If furthermore (3.35) is also substituted in (3.36), one obtains:

\[
e = \frac{m\ddot{x}_H + \beta \hat{m} \dot{x}_H}{m} - (1 + \beta) \hat{x}_H.
\] (3.38)

Recall that \( \hat{x}_H \approx \ddot{x}_H \) is assumed to be valid. Then (3.38) becomes:

\[
e = \beta \left( \frac{\dddot{m}}{m} \dddot{x}_H - \dddot{x}_H \right).
\] (3.39)

Because \( \dddot{x}_H \) can be regarded constant during one cycle, the error dynamics follow as:

\[
\dot{e} = \beta \dddot{m} \dddot{x}_H.
\] (3.40)
Substituting the adaptation law of (3.37) into (3.40) gives:
\[
\dot{e} = -\frac{\beta}{m} \text{sign}(\hat{x}_H) \Gamma \hat{x}_H e.
\] (3.41)

For the purpose of the stability analysis of the equilibrium \( e = 0 \) of (3.41), the following candidate Lyapunov function is adopted:
\[
V = \frac{1}{2} e^2.
\] (3.42)

The time-derivative of \( V \) satisfies:
\[
\dot{V} = e \dot{e} = -\frac{\beta}{m} \text{sign}(\hat{x}_H) \Gamma \hat{x}_H e^2 = -\frac{\beta}{m} |\hat{x}_H| \Gamma e^2.
\] (3.43)

Since \( V > 0, \beta, \Gamma, m > 0, \dot{V}(0) = 0 \) and \( \dot{V}(e \neq 0) < 0 \) if \( \hat{x}_H \neq 0 \), this proves that in the adaptation/enhancement phase \( e = 0 \) is an asymptotic stable equilibrium point provided that the earlier assumptions \( \hat{x}_H \neq 0 \) and \( \hat{x}_H \approx \ddot{x}_H \) are indeed valid. From equation (3.38) it is evident that \( e = 0 \) can only be possible if \( \hat{m} = m \). Therefore convergence of \( \hat{m} \) to the real \( m \) is ensured and consequently so is the convergence of the output of the PAC to the desired value.

If the estimation \( \hat{x}_H \) that follows from (3.23) and (3.24) works and the human operator did not apply any force during the estimation phase \( \ddot{x}(t) = 0 \forall t \in [kT_a, kT_a + T_1] \), then \( \hat{x}_H = 0 \). The latter implies that the error will always be zero according to equation (3.39) despite the fact that possibly \( \hat{m} \neq m \). Therefore, no adaptation of \( \hat{m} \) will occur due to the adaptation law (equation (3.37)) that in this case provides \( \dot{\hat{m}} = 0 \). However, this is not regarded as a problem. If no human force is present, no assistance is required and the controller output will in the case of \( \hat{x}_H = 0 \) indeed provide zero force according to equation (3.28).

Note that the given stability proof that ensures convergence of \( \hat{m} \) to \( m \) depends on several assumptions. These assumptions are based on approximations that in practice will be subject to deviations. Therefore, in practice \( \hat{m} \) will more likely converge to close proximity of the real value of \( m \) instead of ending in the exact value of \( m \).

3.3.3 Timescale implementation

As already shown in the previous sections, for the NFE controller as well as for the PAC, it is important that a proper timescale is chosen for the total cyclic execution rate of the algorithm. When choosing the algorithm execution frequency \( f_a \), where \( f_a = \frac{1}{T_a} \), three considerations should be made.

Studies have shown that a human can perform a task with a frequency of up to 6Hz [9, 31], which is typically much slower than the sampling frequencies at which robotic control schemes execute. Therefore \( f_a \) should be chosen higher than 6Hz to ensure the controller can track the human force and provide the desired force assisting.

Another reason that the algorithm frequency \( f_a \) should be chosen high enough is related to human perception. Namely, it is not desired that the human operator feels vibrations introduced by the pulse width modulation characteristic of the control input (see Figures 3.2 and 3.3), inherent to both controllers. Some research has been done on human perception of vibrations [23, 31]. In [23] it has been shown that a human subject can feel a vibrating object with frequencies up to 300Hz. However, it is also concluded that the human sensitivity greatly depends on the amplitude of the vibration [23, 31]. The higher the amplitude, the higher the frequency perception limit. And the other way around, a lower amplitude decreases the perceived frequency limit. For
3.4. **NFE Controller versus Power Assisting Controller**

Higher amplitudes the perception is limited at 300 Hz, while for lower amplitudes the perception limit decreases to 40 Hz. Unfortunately, these results are merely based on research related to periodic position signals. Therefore a proper choice of $f_a$ that fits human perception should be empirically determined.

A very important consideration for both controllers is to ensure that $f_a$ is chosen high enough to let:

$$F_H(t) \approx F_H(kT_a) \quad \forall t \in [kT_a, (k+1)T_a],$$

be a valid assumption, i.e. the human force can be regarded constant during one algorithm cycle.

For the NFE controller the importance is already somewhat elaborated in Section 3.3.1. There, the Final Value Theorem is used in combination with the assumption of (3.44). By using both it is shown that:

$$\lim_{t \to \infty} \hat{F}_H(t) = \lim_{s \to 0} H(s), \quad \text{where} \quad H(s) = \frac{\hat{F}_H(s)}{F_H(s)}.$$  

(3.45)

Because $\lim_{s \to 0} H(s) = 1$, this proved that $\lim_{t \to \infty} (F_H(t) - \hat{F}_H(t)) = 0$. This clarifies the importance of (3.44), because else this relation and therefore the proof do not longer hold.

The importance for the proposed Power Assisting Controller is also self-evident. The controller extrapolates $\ddot{x}_H$ with a zero-order hold function in the adaptation/enhancement phase to represent the human operator’s intention to accelerate the load. Therefore, to ensure that the important assumption $\ddot{x}_H \approx \ddot{x}_H$ is indeed valid during the enhancement phase, the time-span covered by the enhancement part of $T_a$ should be small. It is obvious that the longer the time-span of the enhancement phase, the larger the strongly undesired deviation between the real \( \ddot{x}_H \) and the extrapolated estimate \( \hat{x}_H \) will become. In order for the stability proof still to hold, the time-span should be chosen short enough that during the enhancement phase not only \( \ddot{x}_H \approx \ddot{x}_H \) holds with a proper choice of extrapolation, but even that \( \ddot{x}_H \) is indeed constant.

### 3.4 NFE Controller versus Power Assisting Controller

In the previous section the controller approach of [41] as well as the controller approach as proposed by this thesis are both fully introduced. In this section both controller approaches will be compared to emphasize their differences.

The essential features of both controller approaches can be recapitulated as follows. The NFE controller is a robust controller which uses a negative feedback loop to let a certain system output settle at the human operator’s force. The PAC is an adaptive approach which uses an adaptation law to adapt an estimate of the load’s mass, which is used in the model generating a human operator’s force estimate.

Therefore the first difference that should be acknowledged is how both controllers handle the unknown mass of the load. The NFE ignores the mass of the load in its control calculations. However, it does set restrictions to the mass’ load by demanding it to be bounded between predefined minimum and maximum values. Within those bounds, the NFE controller should be tuned to ensure stability and sufficient bandwidth to estimate the human operator’s force in the estimation phase. The PAC on the other hand, does not set any restrictions to the load’s mass. An initial estimate of the mass is set and it will keep on adapting this mass estimate till convergence to close proximity of the real mass is obtained. This difference, the NFE controller neglects the load’s mass while the PAC provides an estimate, could lead to certain advantages, or disadvantages respectively, like:
3.4. NFE CONTROLLER VERSUS POWER ASSISTING CONTROLLER

- The NFE controller provides directly in the first control cycle the required power assistance, i.e. directly in the first cycle the human operator's force is estimated and amplified correctly. Dependent on the gain settings of the PAC and the initial mass estimate with respect to the real mass, it could be that the PAC requires a few cycles till it applies the required force support, i.e. till it estimates and amplifies the human operator's force correctly. However, from the first cycle on also the PAC provides assistance though.

- In the previous section it is noted that it is not exactly known yet how a human operator will experience the pulsewidth modulation nature of both controllers. In case of the PAC when a mass estimate is obtained there could be switched to using more common model-based disturbance observers (see Section 2.3) to estimate the external human operator's force.

- In Section 3.2 it is explicitly stated that for this thesis gravity is neglected. This obviously is a purely theoretical assumption and for real cases this should first be dealt with. Because the gravitational force is directly related to the mass of the load, the control approach of the PAC estimating the mass seems a more intuitive approach to offer a future solution.

- The theory of the PAC to obtain the suitable mass estimate requires that there is a human force signal present which causes acceleration of the load. If not, then the mass estimate will not converge. This was already shown in Section 3.3.2. However, in general this will not be a problem as there is no power assistance required if a human force signal would not satisfy this condition.

- The last issue related to how both controller approaches handle the unknown load's mass is the case of slowly time-varying masses \( m(t) \). While this thesis explicitly denotes the assumption that the load's mass can be regarded as being time-invariant in Section 3.2, there are numerous cases where a load is slowly time-varying but robot assistance could be helpful, like for example: feeding livestock on the go from heavy bags with cattle-fodder, casting liquid metals from a transportable storage in to a mold in a foundry, paint spraying where the paint storage empties etc. As long as:

\[
m(t) \approx m(kT_a) \quad \forall t \in [kT_a, (k+1)T_a],
\]

i.e. the mass can be regarded constant over one cycle, then the stability proofs of both controllers still apply. So both controllers will be able to handle cases where equation (3.46) applies. However for the NFE controller problems arise when \( m(t) \) goes out of the predefined bounds. The PAC just keeps on adapting and if the gain of the adaptation law, \( \Gamma \), is chosen high enough it will be able to keep track and therefore provide the required power assistance.

Another difference is that, despite the required inputs to pseudo-linearize the complete robotic system (robot links, friction etc.), both controllers depend on different feedback information. The feedback used by the NFE controller totally depends on the choices of \( p \) and \( K_i \), as visible in (3.4). Therefore, the NFE controller is able to limit its feedback dependency. For example only velocity feedback is used. The PAC on the other hand, is always dependent on the acceleration feedback information. In the case that the dependency of the NFE controller is limited to only velocity it therefore has a clear advantage, namely that the position measurement only has to be differentiated once. Dependency on certain feedback information could appear to be a disadvantage as obtaining usable feedback information is not always straightforward.
This section has emphasized some differences between the two controller approaches. In the next chapter, simulations will show first results likely to cover some of these inherent differences. In Chapter 5 experimental results are discussed that will improve insight in both controller approaches and will strongly reflect on their differences. Finally, in Chapter 6 the reader will find a comprehensive overview of the inherent differences of both controllers and their related advantages or disadvantages respectively.
Chapter 4

Analysis and comparison of controllers by simulation

4.1 Introduction

In Chapter 3 both control approaches are introduced. This chapter presents a simulation study aiming at evidencing the effectiveness of both. In the next chapter also experimental results are presented.

First in Section 4.2 it is shown that the NFE Controller and the proposed PAC satisfy the research objective as defined in the problem statement. However, these simulations assume ideal circumstances. In practice, robotic setups will not comply to this ideal case. Two important issues that are faced in real setups are analyzed in Section 4.3 and Section 4.4, respectively. First the effect of handling friction by the proposed controllers is discussed. Secondly, the effect of handling noise, due to quantized position measurements, by the controllers is investigated. All simulation cases end with a discussion to compare results and behavior of the controller approaches.

4.2 The ideal case

To prove that the proposed controllers, as introduced in the previous chapter, work, the system (3.1), i.e.:

\[ F_H(t) + u = m\ddot{x}, \quad (4.1) \]

is subjected to a simulation study, where the unknown mass \( m = 125 \text{kg} \). For the purpose of control design it is assumed that the unknown load has a mass within the range of \( m \in [50, 200] \text{kg} \). Suppose that the human operator desires to make the load track the following desired trajectory:

\[ x_d(t) = 0.5\sin(2\pi f_d t) \quad \text{with} \quad f_d = \frac{1}{2} \text{Hz}. \quad (4.2) \]

The human behavior is emulated by a proportional-derivative (PD) controller combined with a low-pass filter. For this purpose the linear transfer function used to model the human in the position control loop is given by:

\[ H_{hum}(s) = \frac{500(1+s)}{2\pi 10^3 s + 1}, \quad s \in \mathbb{C}. \quad (4.3) \]
4.2. THE IDEAL CASE

Then the controller output thus becomes:

\[ u_{FH}(s) = H_{hum}(s)(X_d(s) - X(s)). \]  

(4.4)

However, a real human force obviously has bounds which are incorporated in this simulation as saturation bounds of ±200N at the output of the PD-controller. So the human force \( F_H \) acting on the system becomes:

\[
F_H(t) = \begin{cases} 
200 & \text{if } u_{FH} \geq 200 \\
u_{FH} & \text{if } -200 < u_{FH} < 200 \\
-200 & \text{if } u_{FH} \leq -200 
\end{cases} \]  

(4.5)

This initial simulation case assumes ideal circumstances. For the moment, aspects such as noise, parasitic dynamics, signal quantization etc. are neglected.

4.2.1 Simulation results for the Negative Feedback Estimation (NFE) Controller

First the Negative Feedback Estimation Controller as introduced in Section 3.3.1 is put to the test in simulations. The choice of controller parameters affecting the controller’s performance needs to be addressed. Recall from equation (3.4) that the controller output in the estimation phase is defined as:

\[ u(t) = -\sum_{i=0}^{p} K_i \dot{\eta}^{(i)}, \quad \forall t \in [kT_a, kT_a + T_1]. \]  

(4.6)

The parameters that need to be defined here are \( p \) and \( K_i \). By choosing \( p = 1 \), which means using one integrator for the single force estimation, the controller output during the estimation phase thus becomes:

\[ u(s) = -(K_1 s + K_0)\dot{\eta}(s). \]  

(4.7)

Note that \( \eta(s) = \dot{x}(s) + \dot{x}_0 \), where \( \dot{x}_0 \) is the initial condition. By setting the gain \( K_1 \) to zero, acceleration dependency is avoided. This is preferable as it is commonly known that obtaining a smooth acceleration signal in experimental cases can be difficult. Recall that the estimation of the human operator’s force is based on the limit \( \lim_{s \to 0} H(s) \) of the transfer function from (3.9):

\[ H(s) = \frac{\hat{F}_H(s)}{F_H(s)} = \frac{K_0}{(m + K_p)s^p + K_{p-1}s^{p-1} + \cdots + K_0}, \]  

(4.8)

regarded the human operator’s force can indeed be assumed constant over one algorithm cycle. With the choice of \( p = 1 \) and \( K_1 = 0 \) this becomes:

\[ H(s) = \frac{\hat{F}_H(s)}{F_H(s)} = \frac{K_0}{ms + K_0}. \]  

(4.9)

Therefore the pole of this transfer function is \(-\frac{K_0}{m}\), which ensures the denominator’s polynomial to be Hurwitz as long as \( K_0 \) is chosen to be positive.

From Section 3.3.1 it follows that two other considerations must be made when choosing \( K_0 \). Firstly, the choice must ensure that \(|H(s)| \approx 1\) for the typical frequencies of a human force signal. Secondly, the choice must ensure that the estimate settles within the time span of the estimation phase for the complete range of possible masses.
4.2. THE IDEAL CASE

According to the defined load range in the previous section the maximum mass is \( m_{\text{max}} = 200 \text{kg} \). By setting \( K_0 = 3 \times 10^5 \) the pole for the maximum load lies at \( \frac{K_0}{2\pi m_{\text{max}}} = \frac{3 \times 10^5}{2\pi \times 200} = 239 \text{Hz} \). This satisfies the first consideration since the frequency of the human force is assumed to be lower than 6 Hz.

The algorithm frequency at which the control cycles are executed is set at \( f_a = 100 \text{Hz} \). This should be fast enough to satisfy the considerations presented in Section 3.3.3, especially to ensure the human operator’s force can indeed be assumed constant over one algorithm cycle. Therefore the settling time should be smaller than \( T_1 = 0.005 \text{s} \), which equals the time span of the first phase taking 50\% of a complete cycle. If the transient is within 1\% of its final value it is considered settled, thus by definition:

\[ t_s \text{ The settling time is the time it takes the system transients to decay within 1\% of the set point.} \]

Then looking at the time response the settling time \( t_s \) is easily solved from:

\[ e^{-\frac{K_0}{m} t_s} = 0.01. \tag{4.10} \]

With \( m_{\text{max}} = 200 \text{kg} \) and the choice \( K_0 = 3 \times 10^5 \), \( t_s = 0.0031 \text{s} \). Consequently this choice of \( K_0 \) guarantees \( t_s < T_1 \) for the complete range of possible loads.

The final parameter that should be chosen when using the NFE controller is the gain \( \alpha \) that affects the added force. Here the setting \( \alpha = 3 \) is chosen.

![Figure 4.1: Tracking behavior of the desired position without and with \((t \geq 5s)\) controlled force assistance.](image)

To make a clear distinction between cases in which the controller is active or not, the controller providing assistance is started at \( t = 5s \). Figure 4.1 shows the desired trajectory and the realized trajectory. The human operator alone is obviously not able to let the load follow the desired trajectory. However, it is visualized that when the NFE controller becomes active, the tracking of the desired trajectory is substantially improved. Figures 4.2 and 4.3 show the real human

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29
force and the estimated human force. In Figure 4.2 it is clearly visible that the human operator’s force saturates while attempting to track the desired path. The figure also shows that if the controller starts supporting the human operator, the force that needs to be applied by the operator decreases significantly and therefore it does no longer saturate. Clearly this is due to the controller estimating and amplifying the operator’s force correctly. Figure 4.3 shows a zoomed part of the operator’s force estimation performed by the controller. Each time at the start of an estimation phase the force estimate \( \hat{F}_H \) converges from the previous estimated value, which is kept constant during the amplification phase, to \( F_H \).

![Figure 4.2: Disappearing saturation of human operator’s force when the force estimation acts properly.](image)

This simulation illustrates that the approach using the Negative Feedback Estimation Controller gives satisfactory results according to the problem statement. It provides scaled human power assistance by human operator’s force estimation for a certain bounded range of unknown masses.

4.2.2 Simulation results for the Power Assisting Controller

Also the newly proposed Power Assisting Controller is subject to a simulation study in the ideal case. The execution frequency of the PAC is chosen identical to the one of the NFE Controller, namely \( f_a = 100Hz \) which again should be fast enough to satisfy the earlier discussed timescale issues. This being said, a proper and logic choice for extrapolation of \( \hat{x}_H \) during the enhancement phase is a zero-order-hold approximation of the last sample from the preceding estimation phase. \( \hat{x} \) is obtained by ideal differentiators. Furthermore the initial estimate of \( \hat{m} \) is set at \( \hat{m}_0 = 60kg \), while the real unknown mass still is \( 125kg \). The convergence rate is influenced by the choice of the gain \( \Gamma \). The setting chosen is \( \Gamma = 1500 \), which should be high enough to result in obtaining a mass estimate in a limited number of algorithm cycles. The desired amplification factor is set identical to the previous simulation with the NFE Controller, namely \( \alpha = 3 \). Again to make a clear distinction between the behavior with and without control, the PAC starts functioning at \( t = 5s \).
4.2. THE IDEAL CASE

The simulation results for the tracked position, the real and enhanced estimated human force and the estimation of the mass are visible in Figures 4.4, 4.5 and 4.6, respectively. First focus on the part that the PAC does not function yet and therefore no aided force besides the human force is present, so $t < 5\text{s}$. Figure 4.5 visualizes that the human force $F_H$ saturates while trying to track the desired trajectory. This corresponds to Figure 4.4 where it is visible that the obtained tracking is not satisfactory.

At $t = 5\text{s}$ the PAC starts acting and instantaneously supporting force is present. Very rapidly $\hat{m}$ converges to the real $m$ as can be seen in Figure 4.6. Therefore the controller estimates and adds an amplified version of $F_H$ correctly as can be seen in Figure 4.5. With this additional force saturations of $F_H$ no longer occur. The result is that the desired trajectory is tracked with significant improvement in tracking accuracy and that the human force decreases significantly.

Presenting a zoomed version of Figure 4.6 in Figure 4.7 reveals behavior that requires some analysis. According to the analysis of Section 3.3.2 $\hat{m}$ should converge to close proximity of $m$. However, in Figure 4.7 $\hat{m}$ clearly shows a periodic deviation around the real value of $m$. This behavior can be explained as follows.

During the analysis of Section 3.3.2 it is assumed that the frequency $f_a$ at which the PAC algorithm executes is chosen high enough. Then $\ddot{x}_H$ can be regarded as being constant during the time-span of the enhancement phase. Based on this assumption $\ddot{\hat{x}}_H$ used in the algorithm during the enhancement phase is held constant by applying a zero-order-hold to the last sample of the preceding estimation phase. Recapitulating the error used in the adaptation law for $\hat{m}$ as defined by equation (3.36) gives:

$$e = \frac{m\ddot{x}_H + \alpha \hat{m} \ddot{\hat{x}}_H}{\hat{m}} - (1 + \alpha) \ddot{\hat{x}}_H,$$

which can be rewritten as:

$$e = (\ddot{x}_H - \ddot{\hat{x}}_H) + \alpha (\hat{m} - 1) \ddot{\hat{x}}_H.$$  (4.12)
If the assumption previous stated is valid, i.e. $\ddot{x}_H$ can be regarded constant during the enhancement phase, then the applied zero-order-hold to obtain $\ddot{\hat{x}}_H \approx \ddot{x}_H$ suffices. This causes the first term of the error in equation (4.12) to become zero. With the error that remains, the analysis from the previous section that ensures convergence of $\hat{m}$ to $m$ holds. However, it is obvious that this assumption is only approximately true. $\ddot{x}_H$ will not be exactly constant during the enhancement phase. At the beginning of the phase the first term is indeed approximately zero. During progression of the enhancement phase the deviation between the estimated acceleration $\ddot{\hat{x}}_H$ and the real human acceleration $\ddot{x}_H$ will increase. The effect of mismatch between $\ddot{x}_H$ and $\ddot{\hat{x}}_H$ on to the adaptation of $\hat{m}$ depends on the balance between the first term and the second term of equation (4.12).
4.2. THE IDEAL CASE

To support the previous analysis, Figures 4.8 and 4.9 show the difference between $\ddot{x}_H$ and $\hat{\ddot{x}}_H$ covering approximately two complete cycles. In Figure 4.8 it can be observed that, except for a small deviation caused by phase delay introduced by the differentiation filters, $\ddot{x}_H \approx \hat{\ddot{x}}_H$ during the estimation phase. During the enhancement phase, where $\hat{x}_H$ is held constant, the deviation is increasing. In Figure 4.9 the first term of error equation (4.12) is presented. Due to the phase shift it is not exactly zero during the estimation phase and at the start of the enhancement phase. The sign and growth rate of the first term in the error equation, and therefore its effect on $\hat{m}$, depends completely on the human input $F_H(t)$. Therefore the deviation of $\hat{m}$ around $m$ as visible in Figure 4.7 has a periodic cycle that has a direct relation with $F_H(t)$ and thus with $x_d(t)$ as defined in equation (4.2) to which $F_H(t)$ is directly related.

So the occurring behavior in $\hat{m}(t)$ depends on the kind of human force signal and the acceleration it realizes. To show that the effect of this is not significant compared to the result that is intended, namely adding force to the unknown mass that is approximately equal to $\beta F_H$, some other human force inputs are simulated. The results can be found in appendix A.

Furthermore this undesired behavior can be greatly reduced by introducing the following improvements:

- Increasing $f_a$ to shorten the enhancement phase. This limits the growth of the deviation between $\ddot{x}_H$ and $\hat{\ddot{x}}_H$.

- Make $\Gamma$ error dependent, i.e. $\Gamma(e)$. This ensures fast convergence of $\hat{m}$ when it has a significant deviation from the real $m$, i.e. when a large error $e$ is present, which will be the case at the start of the power assisting. However, if $\hat{m}$ has converged to a range that $\hat{m} \approx m$, the second term of the error in equation (4.12) will be small and therefore the first term becomes more significant. Therefore a smaller $\Gamma$ when the error is within certain bounds, leads to decreased sensitivity for the described effect.

- Make $\Gamma$ depend of the time progressing during the enhancement phase, i.e. $\Gamma(t_{\text{enhancement}})$. At the start of the enhancement phase the assumption $\ddot{x}_H \approx \hat{x}_H$ is valid and therefore $\Gamma$ should be large because the occurring error is solely due to the mismatch between $\hat{m}$ and $m$. During progress of the enhancement phase in the balance of the complete error the mismatch effect becomes more significant and therefore $\Gamma$ should decrease to make it less sensitive.

The simulation of the Power Assisting Controller also shows satisfactory results that comply with the problem statement. The human operator’s force is estimated correctly. The mass estimate converges properly as expected, despite an initial estimate with a significant deviation of the real mass value. The fact that the human operator’s force is estimated correctly implies that the additional force provided by the controller is, as desired, an amplified version of the human operator’s force.

4.2.3 Comparison of results

For the ideal case both controllers offer a solution for the problem statement. It is interesting to compare Figures 4.2 and 4.5. It can be observed that both controllers, after transients, provide the same additional force which indeed should be the case because for both controllers $\alpha = 3$.

The NFE Controller has the advantage that it already in the first cycle directly estimates $F_H$ and therefore directly provides the desired additional force. The PAC on the other hand also
4.3. THE EFFECT OF FRICTION DISTURBANCES

directly adds a force to help the operator. However, before \( \hat{m} \) has converged this added force is not the desired amplified version of the human operator’s force. By choosing \( \Gamma \) large enough \( \hat{m} \) will converge fast enough to minimize this effect.

A disadvantage of the NFE Controller is directly related to this. The NFE controller is robust for certain bounds on the mass. The NFE controller’s gain parameters have to be chosen to accommodate the complete range of masses. If the upper bound of the possible masses is not really known, high gains should be chosen. This could result in saturated control inputs for the NFE controller if the real mass is much lower then the expected maximum mass. The PAC is not subjected to bounds on possible masses. If the initial estimate \( \hat{m} \) is way off, it will just take some more time before convergence of \( \hat{m} \) to \( m \) has been achieved.

4.3 The effect of friction disturbances

An aspect that is worth studying is the presence of friction in a real robotic setup. If friction is introduced in the model, equation (4.1) transforms in to:

\[
F_H(t) + u = m\ddot{x} + F_{fric}(\dot{x}),
\]

(4.13)

where \( F_{fric}(\dot{x}) \) represents the force due to friction which is assumed to be mainly velocity dependent. The friction force is modeled by the following equation:

\[
F_{fric}(\dot{x}) = B_v\dot{x} + B_{f1}\left(1 - \frac{2}{1 + e^{2w_1\dot{x}}}\right) + B_{f2}\left(1 - \frac{2}{1 + e^{2w_2\dot{x}}}\right),
\]

(4.14)

with:

\[
B_v = 97.26\frac{Ns}{m}, \quad B_{f1} = 54.9912N, \quad B_{f2} = 46.5915N,
\]

\[
w_1 = 150.3190, \quad w_2 = -98.9881.
\]

The friction model covers viscous, Coulomb and Stribeck effects and therefore can provide a realistic representation of the friction present in a real robotic setup.

For both controllers all adjustable parameters are identical to those in Section 4.2. Furthermore, a new definition is introduced:

\[
F_r(t, \dot{x}) := F_H(t) - F_{fric}(\dot{x}).
\]

(4.15)

Thus \( F_r \) represents the residual force that remains after the friction force is subtracted from the human operator’s force. It is expected that both controllers will estimate the residual force \( F_r \) instead of \( F_H \). Therefore it might be wise to use modeled friction compensation in real setups. However, this also has drawbacks because first an identification experiment needs to be performed and even then a compensation model will never compensate exactly for all system friction present. In the case of friction overcompensation, due to an inaccurate friction model, even additional undesired dynamics is introduced which could cause problems. Therefore friction compensation is omitted in the following simulated friction cases.

\[\text{This friction model and the corresponding parameter values are based on an identification, performed in [6], of the robotic setup as used for real experiments in the next chapter.}\]
4.3.1 Simulation results of the Negative Feedback Estimation (NFE) Controller

The simulation results are presented in the same kind of figures as in the previous section. Figures 4.10, 4.11 and 4.12 show the tracked position, the real force and its estimation and a zoomed version of these forces respectively.

The NFE Controller estimates the external force applied on the system. However, this force is now counteracted by the friction present in the system. The residual force $F_r$ is the force that...
remains being applied. Therefore $F_r$ is the force that is estimated by the NFE Controller as can be seen in Figure 4.11. Here the friction force is of such a proportion that if the residual force $F_r$ is estimated and amplified the human operator’s force still gets enough help to prevent it from saturating.

4.3.2 Simulation results of the Power Assisting Controller

Next the Power Assisting Controller is used in a simulation with friction. The results of simulating the model of equation (4.13) and the PAC, with all parameters identical to the simulation as in Section 4.2, are visible in Figures 4.13, 4.14 and 4.15 for position tracking, force estimation and mass estimation, respectively. Obviously, the PAC also estimates $F_r$ instead of $F_H$ and will therefore add less force than required according to the problem statement. However, the human operator will still experience additional force support while performing its task.

4.3.3 Discussion

The friction force counteracts the human operator’s force. If no friction compensation is present both controllers will regard the residual force $F_r = F_H(t) - F_{friec}(x)$ as the external force to be estimated. This is clearly visible in Figures 4.12 and 4.14. So friction will decrease the controller output and therefore the effect of power-assisting felt by the human operator.

Therefore friction compensation is desired. However, care must be taken. If the real friction is slightly overcompensated this overcompensation will result in a force residue that is amplified by the controllers. This could cause the system to become unstable. To prevent this from happening, it must be ensured that the friction compensation is lower than the real friction.

Note that if the applied controllers estimate the residual force $F_r$ this can offer new perspectives for other applications. If there is no human force present (i.e. $F_H = 0$) and an additional control force to move the mass is known, then such controller can offer an identification method.
4.4 The effect of quantized position measurements

In a real setup the position feedback signal is measured by encoders. These encoders have a limited resolution. It is this limited encoder resolution that causes the position measurement to be quantized. This quantized position measurement is the main cause for 'noise' on the measured position signal. In the following sections, both controller approaches have to cope with quantized position signals. All settings from the tunable control parameters are similar to the case of Section 4.2.

4.4.1 Simulation results of the Negative Feedback Estimation (NFE) Controller

With the settings of Section 4.2 the NFE controller in the estimation phase only depends on velocity information. This velocity information needs to be obtained by differentiation of the position measurement. However, this differentiation will amplify the noise present in the position measurement. Therefore a low-pass filter with cut-off frequency $f_c$ is implemented as:

$$H_{L1}(s) = \frac{\omega_n^2}{s^2 + 2\xi \omega_n s + \omega_n^2} \quad \text{where} \quad \omega_n = 2\pi f_c, \quad f_c = 75Hz, \quad \xi = 1.$$  \hspace{1cm} (4.16)

The position tracking is shown in Figure 4.16. Figures 4.17 and 4.18 show the real and estimated human operator’s force respectively. Again the estimation algorithm, and therefore the desired assistance, shows satisfactory results. However, the results are clearly affected by the measurement noise due to quantization.
4.4. THE EFFECT OF QUANTIZED POSITION MEASUREMENTS

Figure 4.16: Tracking behavior of the desired position without and with \((t \geq 5\, \text{s})\) controlled force assistance affected by measurement quantization.

Figure 4.17: Disappearing saturation of human operator’s force when the force estimation acts.

Figure 4.18: The human force estimate is clearly affected by noise.

4.4.2 Simulation results of the Power Assisting Controller

Due to the required acceleration information feedback, the PAC is also subjected to the problem of greatly amplifying high-frequent measurement noise by differentiation. There are several solutions available in literature that filter the noise or avoid differentiation by using observers to minimize this noise amplification. However most of them are not suitable for the proposed PAC. Either they use model information, which is not available according to the problem statement, in the form of observers to obtain acceleration information or they obtain acceleration by offline
4.4. THE EFFECT OF QUANTIZED POSITION MEASUREMENTS

batch filtering while the PAC requires realtime online filtering.

The solution that remains is introducing standard realtime low-pass filtering. By doing so a conflicting trade-off appears. The characteristic cut-off frequency $f_c$ of the chosen low-pass filter determines which frequencies with undesired noise are suppressed. Taking in to account which frequencies the human behavior will cover, $f_c$ should be chosen quite low to get good sufficient noise reduction and guarantee a sufficiently accurate acceleration estimate $\hat{x}$. However, the side-effect of choosing $f_c$ low, is that the filter will become slow in tracking with a significant delay. In most cases the trade-off is made and $f_c$ can be chosen to satisfy both constraints, i.e. good enough noise reduction and still fast enough tracking.

The proposed PAC introduces an additional obstacle that makes the trade-off much more complicated. The PAC acts in a cyclic fashion consisting of the two separate phases. In the first estimation phase no force is added (see Figure 3.4) and therefore the acceleration is $\ddot{x} = \ddot{x}_H$. During the enhancement phase, instantaneously an extra force is added to the system which causes the acceleration also instantly to become $\ddot{x} = \ddot{x}_H + \frac{\alpha n m}{m} \dot{\hat{x}}_H$. This means that each time a transition between the two phases occurs, a significant step in the acceleration is observed which induces very high frequencies. This reveals the obstacle introduced by the proposed PAC. On the one hand the PAC needs very good noise suppression, so choosing $f_c$ very low, because quantization noise will directly affect the adaptation of $\hat{m}$ and the estimate $\hat{\ddot{x}}_H$. And thus it will affect the assisting force. On the other hand to ensure that the estimate $\hat{x}$ is able to follow the steps that occur at the phase transitions, the cut-off frequency should be chosen very high.

Despite these contradictory demands, noise suppression at higher frequencies is an unavoidable necessity. This being said, the delay introduced by the filter results in a certain settling time after each step in acceleration. So after a transition between phases has occurred, the acceleration estimate $\hat{x}$ needs some time to settle before it represents the actual and therefore usable acceleration again.

Recapitulate the definition of settling time used in this thesis:

- **The settling time** $t_s$ is the time it takes the system transients to decay within 1% of the set point.

It is required that $t_s << T_1$ to be able to obtain a usable representative acceleration estimate $\hat{x}$ before the end of the estimation phase. Note that the estimation phase $T_1$ is much smaller than the succeeding enhancement phase. If a certain level of noise reduction must be obtained and therefore a certain low choice of $f_c$ is mandatory, $t_s$ follows as a characteristic of the filter. This $t_s$ should still satisfy $t_s << T_1$. Because $t_s$ is a characteristic that follows from the mandatory choice of $f_c$, only a proper choice of $T_a$ and therefore resulting $T_1$ can still guarantee $t_s << T_1$. However this introduces a new trade-off. In Section 3.3.3 it was shown that in order for the PAC to function properly, the time-span $T_a$ should be chosen short enough such that during the enhancement phase not only $\dot{\hat{x}}_H \approx \dot{x}_H$ holds with a proper choice of extrapolation, but even that $\ddot{\hat{x}}_H$ can be regarded as being approximately constant. The effect of violating this assumption is shown in the simulations of Section 4.2.2. So this reveals the new trade-off. If $T_a$ should be chosen larger to satisfy $t_s << T_1$ then this also increases the undesired effect of $\ddot{\hat{x}}_H \approx \ddot{x}_H$ not being valid during progress of the enhancement phase. Besides this, increasing $T_a$ could result in the human operator perceiving the frequency at which the algorithm executes. This is obviously undesired.
4.4. THE EFFECT OF QUANTIZED POSITION MEASUREMENTS

To get some more insight in this trade-off the low-pass filter used is chosen to be:

\[ H_L(s) = \left( \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} \right)^2 \quad \text{where} \quad \omega_n = 2\pi f_c, \quad \xi = 1, \quad (4.17) \]

and the trade-off between the choice of \( f_c \) and \( T_a \) is presented in Figures 4.19 and 4.20. Figure 4.19 shows the characteristic \( t_s \) that relates to the choice of \( f_c \). If \( T_1 = 0.3T_a \) Figure 4.20 shows \( T_a \) for which \( T_1 \) equals the time necessary to settle, so \( t_s \). This graph thus restricts the choice of \( T_a \) if \( f_c \) is chosen. \( T_a \) should be chosen higher than the value that follows from the graph to ensure that the estimation signal \( \hat{x} \) has settled and represents approximately the true value of \( \ddot{x} \) within the time-span covered by the estimation phase \( T_1 \).

![Figure 4.19: Settling time as a function of \( f_c \). Figure 4.20: Minimal \( T_a \) to ensure that \( T_1 \geq t_s \).](image)

To show that the PAC can handle measurement noise due to quantized position measurement a simulation is performed. The simulation setup is identical to the one performed in Section 4.2; only now the used position measurement is quantized with an encoder resolution\(^2\) of \( 5.0 \times 10^{-6} \text{ pulse/m} \). This requires some adaptation of the controller scheme. To obtain the acceleration \( \ddot{x} \) a filter is used as:

\[ H(s) = \left( \frac{\omega_n^2 s}{s^2 + 2\xi\omega_n s + \omega_n^2} \right)^2 \quad \text{where} \quad \omega_n = 2\pi f_c, \quad f_c = 75Hz \quad \xi = 1. \quad (4.18) \]

If \( f_c \) is chosen at 75\( Hz \) it follows from figure 4.19 that \( t_s \approx 0.022s \). To ensure that \( \hat{x} \) has settled during the estimation phase, \( T_1 \) should take longer than \( t_s \). Therefore \( T_1 \) is set to take 5% longer then \( t_s \), so \( T_1 = 0.0231s \). With the estimation phase covering 30% of the total cycle, \( T_a \) becomes 0.0770s which is approximately an execution rate of \( f_a \approx 13Hz \).

The force is still immediately added by the PAC from the start of the enhancement phase. However, an adjustment made to cope with the settle time is that after the phase transition has occurred, \( t_s \) seconds is waited before \( \hat{x} \) is trusted to be representative and the update law for adapting \( \hat{m} \) is applied.

\(^2\)The chosen encoder resolution is as in the robotic setup as used for experiments in the next chapter.
4.4. THE EFFECT OF QUANTIZED POSITION MEASUREMENTS

All other parameters are set equal to those in the previous simulation. Thus the initial estimate of \( \hat{m} \) is set at \( \hat{m}_0(t) = 60\, \text{kg} \), \( \Gamma = 1500 \), the desired amplification factor \( \alpha = 3 \) and the PAC becomes active at \( t = 5s \).

The results of the position tracking, aided human force estimation and mass estimation are respectively presented in Figures 4.21, 4.22 and 4.23. Compared to the simulation results of Section 4.2 the results are clearly affected by the introduced quantization noise. Note that in Figure 4.23 the small ripples are due to the introduced noise and the larger ripples reflect the periodic behavior as already discussed in Section 4.2.2. Despite the visible noise influence, the force assisting by the PAC still seems to function quite well if some introduced vibrations are accepted. Experiments on a real set-up should provide a good balance between sufficient noise suppression and a fast execution rate \( f_a \) by manually tuning the choice of \( f_c \) from which a minimum \( T_a \) will result. Hereby it must be noticed that at lower accelerations the signal-to-noise ratio will deteriorate and vice versa. This is important with respect to the expected amplitude of accelerations obtained, which will obviously depend on the human’s intentions and the mass of the load.

![Figure 4.21: Tracking behavior of the desired position without and with (\( t \geq 5s \)) controlled force assistance affected by measurement quantization.](image1)

![Figure 4.22: Disappearing saturation of human operator’s force when the force estimation acts properly.](image2)
4.4.3 Discussion

This simulation clearly reveals an advantage in favor of the NFE controller against the PAC. By using the NFE controller it is possible, by choice of control parameters, to limit estimates feedback dependency to velocity information. The PAC needs acceleration information and therefore it is unavoidable to differentiate the position measurements twice. This is obviously undesired due to the strong amplification of noise. The PAC is sensitive for this amplified noise as it flows through the error and update law into the mass estimate \( \hat{m} \). This noise fluctuations in \( \hat{m} \) are directly reflected in the operator’s force estimate \( \hat{F}_H \) and therefore in the added support.

Note that this advantage for the NFE controller only holds for an one degree-of-freedom set-up. For multiple degrees-of-freedom both controllers need an additional controller block to pseudo-linearize the complete system, i.e. to compensate for all robot link dynamics except for the load. To be able to do this, the link dynamics compensation model requires acceleration feedback to calculate inertial forces. This is a problem that needs to be addressed in future work. For this thesis the problem statement is limited to the one degree-of-freedom case.
Chapter 5

Proof of Concept by experimental implementation

5.1 Introduction

In the previous chapters two control strategies, both aiming at delivering scaled force support to a human operator, are introduced. In Chapter 4 results are shown by simulations. The next step is to verify their effectiveness and validate their design by implementation on a real experimental robotic setup.

The experimental setup used for this purpose is a CFT transposer robot as present in the dynamics and control laboratory of the mechanical engineering department at the Eindhoven University of Technology. Despite the fact that the robot has multiple degrees of freedom, in this research only one degree of freedom is used. The experimental setup, including the CFT transposer robot, is fully introduced in Section 5.2. Hereafter, several experimental results are discussed in Section 5.3 and Section 5.4 for the NFE controller and the PAC, respectively. The chapter finishes with a discussion of all the experimental results in Section 5.5.

5.2 Experimental setup

The CFT-transposer robot is a Cartesian robot with a basic elbow configuration, initially designed and built by the Philips Center for Manufacturing Technology. The robot consists of a two link arm which is placed on a rotating base, see Figure 5.1. This rotating base is placed on a translational moving slide. The outer link has a passively actuated tool connected to it, that is designed to keep a horizontal plane at all time.

The robot has seven degrees of freedom in joint space which are actuated by four DC brushless servomotors. In Cartesian space the robot possesses four degrees of freedom which are rotation, up and down or forward backward movement of the end effector and forward and backward movement of the complete robot by the translational slide, see Figure 5.1.
5.2. EXPERIMENTAL SETUP

Despite the fact that the CFT robot has four degrees of freedom in Cartesian space, in this initial study only one degree of freedom is used. The degree of freedom used here is the translational movement of the slide, which means that a single actuated mass is considered. All other joints are manually ‘locked’ by high-gain PD control which is considered rigid.

Based on [6] the total mass of the robot is approximately $128\text{kg}$. Furthermore, all other parameters of importance related to this single degree of freedom are listed in Table 5.1. These parameters include the encoder scaling factor between the pulses of the encoder and their respective measurements, the position limits of the slide, the gear ratio $K_g$ and a conversion ratio $K_c$ that (after gear reduction) relates the rotational movement to the translational movement. Furthermore all the motors are fed by servoamplifiers with a sensitivity of $K_a = 0.4 \frac{A}{V}$. According to the fabrication sheet [6] the motors have a torque constant of $K_t = 0.107 \frac{Nm}{A}$. Therefore the gain from the applied voltage in the servoamplifier to the torque in the motor is $K_v = 0.0428 \frac{Nm}{V}$. Then the total gain from the voltage applied to the servo amplifiers to the force in the respective coordinate is calculated as $K_T = \frac{K_a K_t K_v}{K_c K_g}$.

![Figure 5.1: The CFT-transposer robot.](image)

<table>
<thead>
<tr>
<th>Encoder scaling factor</th>
<th>min. limit</th>
<th>max. limit</th>
<th>gear ratio $K_g$</th>
<th>conversion ratio $K_c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$5.0 \times 10^{-6}$</td>
<td>$-0.55m$</td>
<td>$0.05m$</td>
<td>$\frac{1}{\pi}$</td>
<td>$\frac{0.06 , m}{2\pi , rad}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$K_a$</th>
<th>$K_t$</th>
<th>$K_v$</th>
<th>total gain $K_T$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0.4 \frac{A}{V}$</td>
<td>$0.107 \frac{Nm}{A}$</td>
<td>$0.0428 \frac{Nm}{V}$</td>
<td>$26.8920 \frac{N}{V}$</td>
</tr>
</tbody>
</table>

Table 5.1: Relevant parameter values of the CFT-transposer robot [6].

Finally, the interface and connection between a desktop computer and the robot is provided
5.3 Experimental Results NFE Controller

The development of the NFE controller approach as proposed in [41] and introduced in Chapter 3 is still in its early stages. This also implies that validation on an experimental setup had not been performed yet. This research will implement the NFE controller to gather more experimental insights and to be able to compare both controllers.

5.3.1 Original controller trial

First the controller parameters need to be set. Similar settings are chosen as for the simulations in Section 4.2.1. The desired amplification factor $\alpha$ is set to $\alpha = 2$. Furthermore $p = 1$, so that the controller output during the estimation phase thus becomes:

$$u = -(K_1 s + K_0) \eta, \quad \text{where} \quad \eta = \dot{x}.$$  \hfill (5.2)

To obtain acceleration estimates, applying double differentiation to the position feedback is necessary. It is preferred to avoid this as it is commonly known that obtaining a smooth acceleration
feedback is therefore not always straightforward. The double differentiation will amplify the signal noise significantly. To avoid the use of acceleration estimates, gain $K_1$ is set to zero. Therefore the transfer function between human force and the human force estimate then equals:

$$H(s) = \frac{F_H(s)}{K_0 ms + K_0}.$$  (5.3)

The algorithm cycles are set to function at $f_a = 100 \text{Hz}$, which should be fast enough to assume that the human force is approximately constant over one cycle, and the estimation phase $T_1$ is exactly half of a complete cycle (i.e. $T_1 = 0.005s$). Furthermore, with the real mass known to be $128kg$ the gain $K_0$ that gives a settling time which reduces the initial error to 1% and that satisfies $t_s < T_1$ can be solved from the time response:

$$e^{-\frac{K_0}{m} t_s} = 0.01.$$  (5.4)

This shows that the gain should be chosen very large. For example, a gain of $K_0 = 150 \times 10^3$ satisfies the condition $t_s < T_1$ with a settling time of 0.0039s. However, from a measurement noise sensitivity point of view such a high gain is undesirable, as it will amplify the measurement noise present in the velocity estimate $\dot{x}$. Therefore, to reduce the measurement noise in the obtained velocity estimate, a low-pass filter with cut-off frequency $f_c$ is used described by the transfer function:

$$H_L(s) = \frac{\omega_n^2}{s^2 + 2\xi \omega_n s + \omega_n^2} \quad \text{where} \quad \omega_n = 2\pi f_c, \quad f_c = 50 \text{Hz}, \quad \xi = 1.$$  (5.5)

Implementing this low-pass filter introduces an additional delay which results in a longer settling time before $\hat{F}_H \approx F_H$. It is even more important to note that even with the use of a low-pass filter, noise will be present in the estimated velocity $\dot{x}$. Some first experiments showed that the noise level of the obtained velocity estimate $\dot{x}$ is significant. Therefore using the high gains (i.e. $K_0 = 150 \times 10^3$) required to settle within the estimation phase are highly undesired as they will amplify the noise present in $\dot{x}$. Obviously lowering the algorithm execution frequency $f_a$ diminishes the need for high gains as the estimation signal has more time to settle. However, this is not desired for a twofold of reasons. The first is that the human force should approximately be constant over one cycle, which is not longer valid if the cycle length increases. The second aspect is that the human operator might experience undesired vibrations due to the pulse width modulation nature of the algorithm. Therefore, to prevent the high measurement noise sensitivity a low gain is chosen: $K_0 = 1000$. This implies that the estimation $\hat{F}_H$ will by far not be settled within the estimation phase. However, for a first experiment this seems a sensible choice from where the gain $K_0$ can be increased in steps.

A first experiment shows that the robot exhibits vibrations that can be clearly felt and heard by the human operator. Increasing the gain $K_0$ even further increases this phenomenon. There are two possible causes for these undesired vibrations in the system. The first is that the high-feedback gain $K_0$ indeed amplifies the noise in the velocity estimate $\dot{x}$. This seems plausible as increasing $K_0$ clearly affects the experienced level of vibrations. The second possible cause for the vibrations exhibited by the robot, is related to the pulse width modulation nature of the control approach, i.e. related to the phase transitions. Thus far, there is not so much known about how a human will experience the pulse width modulation nature of such a controller approach.

This leads to a second experiment. This experiment is without phase switching and the algorithm stays acting as if it were permanently in the estimation phase. Thus here the pulse width
modulation is eliminated. In this experiment, the human operator clearly feels the robot system counteracting the human’s force as expected in the estimation phase. It is more interesting to notice, however, that if the pulse width modulation nature is eliminated, the vibrations have reduced significantly.

These both experiments result in a first set of conclusions. An increased gain indeed introduces stronger vibrations due to amplification of noise in the estimated velocity signal $\hat{x}$. And furthermore the pulse width modulation is also, partly but significantly, responsible for the strong vibrations exhibited by the robotic system.

To reduce the latter, i.e., the experienced vibrations due to the pulse width modulation, $f_a$ should probably be increased significantly ($f_a > 500Hz$). However, this is not possible as this adaptation will also require an undesired tremendous increase of the gain $K_0$ to be able to still settle within the estimation phase, which in turn would increase the sensitivity to measurement noise.

5.3.2 Adapted NFE Controller by lowering algorithm execution frequency

With the experimental results of the previous section in mind, another experiment is designed to act as a proof-of-concept. With the parameter setting of the previous section (i.e. $\alpha = 2$, $p = 1$, $K_1 = 0$, $K_0 = 1000$, $f_c = 50Hz$) the settling time of the estimation in the first phase takes $t_s \approx 0.6s$. Therefore, if the control algorithm is set to act at a frequency of $f_a = 0.5Hz$ which gives $T_a = 2s$ and thus $T_1 = 1s$, then the estimation $\hat{F}_H$ will settle within the first phase. Furthermore the pulse width modulation will be so slow that the human operator can clearly distinct when a phase transition occurs. While performing such an experiment it should become clear if the controller’s estimation indeed settles at the human operator’s force and if in the amplification phase the required force assistance is obtained.

In this experiment the human operator applies a small force and aims at applying a constant force. During the estimation phase the robot hardly moves as the algorithm counteracts the human operator’s force. When the amplification phase starts, the robot moves very abruptly for a second till a new estimation phase is started. The estimated force signal $\hat{F}_H$ is visible in Figure 5.3. The behavior as exhibited by the human operator’s force estimation satisfies expectations. The signal settles at the end of the estimation phase and obviously is kept constant during the amplification phase. It must be noted that at the start of an estimation phase some transients are present. This is probably due to differentiation issues with samples from different phases, which gives these spikes in $\hat{x}$. To be sure more research is required. For this report it suffices to show that the fundamental idea of cyclic sensorless force estimation and force amplification could work, but some important issues as discovered in the experiments of the previous section have to be overcome. Regarding the latter, the most important is that an experimental setup or methodology is found that gives a merely noiseless velocity estimate $\hat{x}$. If so, then the algorithm frequency as well as the control gains can be increased significantly as necessary. This should make the algorithm work.

5.4 Experimental results PAC

The PAC as proposed in this report is also subjected to experimental trials. Again the goal is to provide a proof-of-concept for this specific control approach. Because from the identification performed in the work of [6] the real mass is known to be approximately 128kg, the PAC should
adapt \( \hat{m} \) to converge to a proximity of this value. If \( \hat{m} \) does so and the human operator clearly experiences force support, then this can be regarded as a promising first experimental validation.

5.4.1 Original controller trial

Initially the objective of the first experiment is to test the PAC in its form as introduced in Chapter 3, whereby the parameters settings are \( f_a = 100 \text{Hz} \), \( \Gamma = 1500 \) and \( \alpha = 2 \). However, a significant problem arises. The obtained acceleration estimate \( \hat{\ddot{x}} \) is significantly affected by noise. Therefore, the first experiments performed with a noisy \( \hat{\ddot{x}} \) do not give satisfactory results. This is explained by noticing that any noise is directly related to the adaptation error which is based on accelerations (see equation (3.36)), and therefore noise is directly fed through the adaptation law to wrongly adapt \( \hat{m} \) (equation 3.37). As \( \hat{m} \) is directly used in calculation of the required and added control force, the noise in the estimated acceleration is thus directly fed back into the system. To obtain a good acceleration estimate \( \hat{\ddot{x}} \) is a problem that hinders complete implementation of the PAC algorithm.

A first option to offer a solution is the implementation of low-pass filtering. However, as seen before, low-pass filtering introduces a delay and requires significant settling time of \( \hat{\ddot{x}} \) after a phase transition. Hence, the following tradeoff occurs. To obtain sufficiently good noise suppression the cut-off frequency of a low-pass filter should be chosen low enough. However, by decreasing the cut-off frequency the settling time increases and thus after each phase transition it takes longer before \( \hat{\ddot{x}} \) correctly tracks the occurred step in the real acceleration. The signal \( \hat{\ddot{x}} \) should be settled within the first phase \( T_1 \), which makes up 30\% of a complete cycle period \( T_a \). However, recall from Section 3.3.3 that the algorithm frequency \( f_a \) at which the cycles execute should be chosen sufficiently high to avoid the human feeling vibrations at this frequency. Therefore the time-span \( T_a \) and thus \( T_1 \) are restricted in length. When trying to let the algorithm execute at \( f_a = 100 \text{Hz} \), it is not possible to find a corresponding cut-off frequency for a low-pass filter that gives sufficient noise suppression and still ensures a settling time \( t_s \) smaller then \( T_1 \).
5.4. EXPERIMENTAL RESULTS PAC

(i.e. \( t_s < T_1 \)).

Two possible adaptations to circumvent this tradeoff are experimentally tested and worth to be briefly mentioned.

The first idea is splitting the acceleration estimate \( \hat{x} \) into two separate acceleration estimates for each phase, \( \hat{x}_1 \) and \( \hat{x}_2 \) for the estimation phase or adaptation/enhancement phase respectively. Remember that the real acceleration has a significant step when a phase transition occurs. In the estimation phase \( \hat{x}_1 \) follows directly from double differentiation of the position samples. In the adaptation/enhancement phase \( \hat{x}_1 \) follows from extrapolation of stored \( \hat{x}_1 \) samples from the last estimation phase. Likewise, \( \hat{x}_2 \) follows directly from differentiation of the position samples in the adaptation/enhancement phase. In the estimation phase it also follows from extrapolation of stored \( \hat{x}_2 \) samples from the last adaptation/enhancement phase. The idea is that the extrapolated estimates, bridging the other phase, end closer to the real first acceleration value of a new phase. So the extrapolation of \( \hat{x}_1 \) during the adaptation/enhancement phase is expected to end closer to the first real acceleration value in a new estimation phase after a phase transition has occurred. Therefore the differentiation algorithm will experience a smaller initial error between the estimate and the real acceleration value, which needs to be closed, at the start of a phase when using the extrapolated estimate. Therefore, the cut-off frequency of a used low-pass filter to filter measurement noise can be chosen loser as the error to overcome is less significant and it therefore takes less time to end in proximity of the real acceleration value. This reasoning is homogeneous for the case of \( \hat{x}_2 \).

Another approach trying to cope with the problem of proper noise reduction is using the time stamping concept [30]. The time stamping concept consists of capturing position encoder events, consisting of the position encoder transitions and their time instants. Polynomial interpolation through a defined number of encoder events and extrapolation make it possible to estimate the encoder position, velocity and acceleration. In [30] the authors extend this concept by introducing a skip option to skip a defined number of encoder events. This increases the time-span and therefore improves estimation results by decreasing the effect of quantization errors. However, this concept is not applicable to track the steps in acceleration that occur at phase transitions when the PAC is implemented. Therefore, again two separate polynomials are determined for the acceleration estimate of each separate phase. The last encoder events from the previous equal phase are transposed to let the polynomial estimate align again with the first measured samples in the new phase. This approach to obtain a good acceleration estimate does not offer a solution, as implementation on the experimental setup does unfortunately not give satisfactory results.

Some other approaches to obtain the acceleration estimate \( \hat{x} \) are not possible to implement. A well-known option for example is the use of observers. These are not applicable as they depend on model information which is unknown according to the problem statement. To still be able to offer a proof-of-concept, in the next section the algorithm frequency \( f_a \) is lowered to increase the period \( T_a \) and therefore to make it possible for \( \hat{x} \) to settle within the phases and still be subject to proper noise suppression.

5.4.2 Adapted PAC, by lowering algorithm execution frequency

Overcoming the issue that, on the one hand, \( \hat{x} \) needs to settle very fast (due to high \( f_a \)), after a phase transition has occurred, and, on the other hand, proper noise suppression is still ensured seems not possible. However, to still provide a partial proof-of-concept it is proposed to filter the acceleration with a low-pass filter with a significant low cut-off frequency. Then, to cope with the correlated increased settling time of \( \hat{x} \) after phase transitions, \( T_a \) has to be increased accord-
5.4. EXPERIMENTAL RESULTS PAC

ingly. The side-effect will probably be that the human operator will feel some of the pulse-width-modulation nature of the algorithm, but just for the proof-of-concept this is taken for granted. The following adaptations are introduced.

To obtain the acceleration estimate \( \hat{\ddot{x}} \) the following filter is used:

\[
H(s) = \left( \frac{\omega_n^2 s}{s^2 + 2\xi \omega_n s + \omega_n^2} \right)^2 \quad \text{where} \quad \omega_n = 2\pi f_c, \quad f_c = 20 \text{Hz} \quad \xi = 1. \tag{5.6}
\]

If \( f_c \) is chosen at 20Hz it follows from Figure 4.19 that \( t_s \approx 0.08s \). To ensure that \( \hat{\dot{x}} \) has settled during the estimation phase, \( T_1 \) should take longer then \( t_s \). From Figure 4.20 it follows that to ensure this, i.e. \( T_1 > t_s \), \( T_a \) should be at least 0.27s. Therefore the algorithm is set to execute at a frequency of \( f_a = 3\text{Hz} \). A last adaptation is that the adaptation law is not applied the first 0.1s after the start of an enhancement phase. This is done because \( \hat{\dot{x}} \) first needs to be settled to be able to obtain a representative error used in the adaptation law.

Unfortunately the experimental results obtained are unsatisfactory. Recall from Chapter 3 the assumption that the human operator’s force \( F_H \) can be regarded constant during one algorithm cycle, i.e.:

\[
F_H(t) \approx F_H(kT_a) \quad \forall t \in [kT_a, (k+1)T_a]. \tag{5.7}
\]

As discussed in Section 3.3.3, this assumption was required for two reasons: first it needs to hold to ensure that the zero-order-hold approximation of \( \hat{x}_H \) in the adaptation/enhancement phase is valid (i.e. \( \hat{x}_H \approx \ddot{x}_H \)), secondly it is required to let the stability proof as given in Section 3.3.2 hold.

However, it is likely that this assumption of equation (5.7) is not valid anymore for the case of \( f_a = 3\text{Hz} \). To show this, the same experiment is performed but with simplified dynamics. The mass estimate is set directly at the real mass value, i.e. \( \hat{m} \approx m \). The dynamics are now simplified because the adaptation law can be set to \( \dot{\hat{m}} = 0 \), i.e. no adaptation of \( \hat{m} \) occurs anymore. Thus a constant control output is provided by the PAC in the enhancement phase as:

\[
u(t) = \beta m \hat{\ddot{x}}_H, \quad \forall t \in [kT_a + T_1, (k+1)T_a]. \tag{5.8}
\]

If this proposed adapted version of the PAC works, then it is expected that the acceleration nicely doubles in the enhancement phase due to the input force that gets doubled. The result is shown in Figure 5.4. As the real acceleration can not be directly measured, the acceleration estimate \( \hat{\ddot{x}} \) is used which, after settling when a phase transition has occurred, should be a good representative. The other shown value, \( \ddot{x}_H \), represents the acceleration due to the human as defined earlier in (3.23) and (3.23). Note that the latter, the real acceleration due to the human, earlier was assumed to be approximately constant over a period cycle.
5.4. EXPERIMENTAL RESULTS PAC

Figure 5.4: Despite the setting \( \hat{m}_0 \approx m \), \( \hat{x} \) is not nicely constant at double the value of \( \hat{x}_H \) during the adaptation/enhancement phases.

Figure 5.5: Without any added control force the estimated human acceleration \( \hat{x}_H \) should in both phases be representative for the acceleration signal \( \hat{x} \) which is not the case.

Figure 5.6: The significant size that the fluctuation obtains clearly shows that \( \hat{x}_H \) is not representative for \( \hat{x} \).

Despite the control input \( u \) being constant during the second phase, the acceleration \( \hat{x} \) clearly is not after the settling time has past. This must be due to the human operator’s force that fluctuates. To show this more clearly, a new experiment is performed. Here no controller input is present and the human moves the robot completely by itself. The estimation algorithm stays the
same, i.e. during the second phase a zero-order-hold is applied to the last estimated acceleration sample of the previous phase 1. Figure 5.5 shows the result. In Figure 5.6 the deviation between the estimated value that the zero-order-hold procedure produces and the other acceleration estimate $\ddot{x}$ that follows from the filter is shown. So, this fluctuation is calculated as:

$$\ddot{x}_{fluc} = \ddot{x} - \ddot{x}_H.$$  

(5.9)

In the figure $\ddot{x}_{fluc}$, which obviously is directly related to $\ddot{x}_H$ and therefore $F_H$, is clearly not constant and thus the assumption of equation (5.7) is indeed not valid for $f_a = 3Hz$.

Unfortunately, the approach of applying a low-pass filter in combination with extending the cycle period $T_a$ is not able to provide a proof-of-concept. In the next section it is tried to avoid the need of low-pass filtering and therefore the delay that requires an extension of $T_a$, by directly obtaining acceleration information from a sensor.

5.4.3 PAC with acceleration sensor

The last approach that should act as a proof-of-concept is mounting an acceleration sensor. This is not completely according to the problem statement of Section 3.2 that restricts the measured feedback to position information. However, mounting an acceleration sensor directly provides the required acceleration information and therefore acts as a work-around for the problem observed in the previous sections. That is, the need of obtaining a good acceleration estimate $\ddot{x}$ by double differentiation of the position measurement in combination with a low-pass filter is eliminated. Therefore, using an acceleration sensor can probably act as a proof-of-concept to show that if a work around is found the PAC does satisfy the problem statement.

Because the human operator’s force typically covers frequencies below 6Hz, the acceleration sensor used should be able to measure these accelerations at low frequencies. Furthermore it should have a small time-delay to avoid all the problems that also result with the time-delay of the low-pass filter. The sensor used is the Hottinger Baldwin Messgerate B12/200. This sensor should satisfy the requirements according to the fabrication sheet [43].

The sensor is mounted directly on to the translational slide. A first simple experiment should validate that the acceleration sensor is able to provide satisfactory measurement results at this experimental setup. Therefore the control input is set to zero and the robot is moved manually by applying human force. The resulting acceleration measurement is visible in Figure 5.7. Obviously, due to all the noise being present, this measurement does not provide the required quality for the acceleration signal; that is a smooth acceleration measurement signal. It is well known that sensors can experience interference that causes such results. However, several experiments are performed that excluded all possible causes of interference like for example servos signals or encoder signals (see Appendix B). These experiments give results in the form of an amplitude spectrum. One spectrum that results of these experiments is shown in Figure 5.8. In this specific experiment the robot (i.e. servos etc.) is off and also encoder readings are off. Therefore the only signal that is present is the acceleration sensor reading and interference can not be present. The robot is moved manually by applying human force. This spectrum, and the others in Appendix B, clearly show that high frequent dynamics appear to be present. The amplitudes due to these dynamics are significant as visible in Figure 5.7, preventing a smooth signal. Thus the measurement of Figure 5.7 is not influenced by noise, but the acceleration sensor measures accelerations due to these parasitic high-frequent dynamics.

These high frequent dynamics could for example be caused by the ball bearings in the rails of the translational slide, or deviations in the rails itself. Another possibility is that the high-frequent
dynamics is introduced by the other robot links. These are 'locked' by high-gain PD control. Therefore they are not really completely rigid but will always be subjected to some flexibility which might introduce these undesired vibrations.

The following conclusion can be drawn. The assumptions that the system acts as a simple single-mass system is not valid for this experimental setup. And for using the acceleration signal that follows from the acceleration sensor, filtering is still required to filter the effects of these parasitic high-frequent dynamics. Thus using an acceleration sensor to directly obtain an useful
acceleration signal does not offer a work-around to avoid the problem with the use of low-pass filtering and the introduced time delay.

5.5 Discussion experimental results

Reviewing the experimental results of the previous sections offers some important insights.

One specific characteristic for both controllers is that they tackle the problem statement of Section 3.2 with an approach that consists of two phases acting in a cyclic fashion. The phase transitions with corresponding force input changes cause significant steps in the required feedback estimates. To still track these signals with a proper estimate within the phases, the estimation has to be sufficiently fast to cope with these steps. However, in all practical setups a position measurement signal will be influenced by noise. Therefore filtering is a necessity. For the NFE controller it is a problem to obtain a proper velocity estimate that is fast enough to track the real velocity. Furthermore the NFE controller also has to choose high gains that make the algorithm force estimation converge fast enough which will also amplify the noise present in the feedback estimations. For the PAC, that is dependent on an acceleration estimate, the problem of obtaining a fast but still proper feedback estimation is even worse due to the double differentiation required.

Obtaining the necessary feedback estimates is thus an essential problem for both controller approaches. Experimental trials on an other experimental setup could be promising though. An experimental setup with a much lower mass will have advantages for both controllers. For the NFE controller this will mean that much lower gains will suffice and therefore the noise present in feedback estimates will not be amplified. For the PAC a lower mass will mean much higher accelerations so that the noise amplitude will be less significant.

Section 5.4.3 showed that what was regarded as noise, most likely due to quantization errors resulting from position encoder resolution, also occurred due to parasitic high-frequent dynamics present in the experimental setup. This means that the simple one degree-of-freedom mass model, on which the controller designs are based, is not appropriate. Mounting an acceleration sensor therefore can not give a nice acceleration signal which should be a direct reflection of the human force, according to the relations used by the PAC as stated in Chapter 3.

Lastly, it should be noted that the assumption that \( f_a = 100 \text{Hz} \) is fast enough to let the human operator and the robot not experience vibrations due to the pulse width modulation nature of the controllers, is not valid according to the experimental experience of Section 5.3.1. This implies that \( f_a \) should be set much higher, what will increase the problems with filtering in relation to introducing time delays and settling times and for the NFE controller that the gains should be increased which is also undesired.

In general, the conclusion of the experiments is that a proper methodology must be found to obtain proper and fast feedback estimates before a real experimental proof-of-concept can be realized. To simplify the latter, obtaining proper and fast feedback estimates, it is recommended that in case of a new experimental setup it has high quality position encoders and less high-frequent parasitic dynamics.
Chapter 6

Conclusions and Recommendations

The creation of a robot that can fulfill complex tasks in a fully autonomous fashion is an ultimate goal in robotics. However, for difficult tasks this is a challenge that is not likely to be solved in the very near future. An intermediate step will be the inclusion of a human operator in the control loop of the robot. A special case of human-robotic cooperation, treated in this thesis, is joint load co-manipulation. While the human provides intelligence and guidance of the load, the robot should provide force assistance.

The report has formulated a specific problem statement for human-robotic load co-manipulation, acting as a guideline for the research work performed. In Section 6.1 the results of this work are reviewed and conclusions are drawn. Based on these conclusions, Section 6.2 follows with recommendations for improvements and further research.

6.1 Conclusions

The problem statement that is formulated and treated in this thesis is the following:

*Design and develop a force-sensorless control strategy that can provide scaled human power assistance by means of a robotic device, while carrying unknown loads.*

Besides the proposed solution in [41], which the report has referred to as NFE controller, there is no solution readily available complying with the problem statement. However, the developments of the NFE controller are just in their early stages and some problems are yet to be overcome. Therefore, in this thesis, an inherently different controller approach is proposed in Chapter 3 named the Power Assisting Controller (PAC). Both controller approaches act in a cyclic fashion consisting of two separate phases. However, despite this similarity both controllers inherently differ. The NFE controller is a controller approach robust for load variations whereby the phases consist of the following:

1. Estimate the human operator force;
2. Apply the scaled force.

On the other hand, the proposed PAC is a controller approach of the adaptive kind, that estimates the mass of the unknown load by applying a proper adaptation law. For the PAC, the two phases therefore consist of the following:
1. Quantifying the human operator’s intention by means of acceleration estimation; the acceleration estimate has a direct relation with the human operator’s force;

2. Estimate the mass of the load by adaptation and simultaneously apply a scaled human force estimate.

These differences in control approach lead to some specific characteristics for each. The NFE controller will directly provide the desired assistance in the first control cycle while the PAC first needs the mass estimate to converge, from which the time this takes depends on the initial mass estimate and the adaptation gain. The NFE controller is robust for a certain range of load masses, i.e. the load mass is subject to predefined bounds. The PAC on the other hand does not set restrictions on the mass of the load. Another characteristic in which both controllers differ is the dependency on feedback estimates. In case of the NFE controller the user is able to define the dependency for certain feedback required. In case of the PAC however, the acceleration feedback estimate is always required. A last characteristic difference to be noted is that the NFE controller requires high-gain feedback while the PAC gives more user influence in setting the adaptation gain. A comprehensive overview of these differences is given in Table 6.1.

Table 6.1: Comprehensive overview of the differences between the NFE controller and the PAC.

<table>
<thead>
<tr>
<th><strong>NFE controller</strong></th>
<th><strong>PAC</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>• robust</td>
<td>• adaptive</td>
</tr>
<tr>
<td>• first cycle direct desired assistance</td>
<td>• direct assistance, after a few cycles correct desired assistance</td>
</tr>
<tr>
<td>• load mass subject to bounds $m \in [m_{min}, m_{max}]$</td>
<td>• no bounds on load mass</td>
</tr>
<tr>
<td>• user-defined dependency on feedback estimates</td>
<td>• acceleration feedback dependent</td>
</tr>
<tr>
<td>• high-gain feedback required to minimize settling time of human force estimate</td>
<td>• adaptation gain $\Gamma$ user-defined</td>
</tr>
</tbody>
</table>

For the NFE controller, theoretically it is shown that if the proper control parameters are set it will estimate the human operator force correctly and subsequent provide the desired force assistance. Also for the PAC it is shown that the estimate of the load mass will converge to close proximity of the real mass and that subsequently the controller will estimate and provide the desired force assistance if certain control conditions are met.

For validation and comparison purposes both controllers are subjected to specific simulation cases and experiments. From the simulation case studies the following conclusions result. The performances of both controllers for an ideal case (i.e. no noise, quantization errors, friction etc.) are satisfactory. That is, for the ideal case both controllers offer a solution for the problem statement of this thesis; they provide a force-sensorless control strategy that provides a desired scaled force estimate despite an unknown load mass being present.

From the other simulations performed, which include the effect of friction and quantization errors in the position measurement, one important issue is revealed which is also the most significant result of the performed experiments. Both controllers require feedback estimates like $\dot{x}$
and $\dot{a}$ of the velocity and acceleration respectively. However, obtaining smooth feedback estimate signals that are fast enough to track the real velocity and acceleration, including the steps in acceleration at phase transitions, and still maintain a proper reduction of the noise level appears to be a significant problem remaining.

Another observation that resulted from the experiments is that the execution of the control algorithms at 100 Hz introduces strong vibrations in the system, which are clearly noticeable by the human operator and harmful for the robotic system. This is due to the pulse width modulation nature of both controllers. This is a valuable result as previously such experimental experience was lacking. To prevent these vibrations the frequency of the algorithm cycles should be significantly increased. However, this makes the previous problem considered even more troublesome.

Despite these encountered problems the idea of the NFE controller seems promising. By drastically decreasing the algorithm frequency it is shown that the force estimate indeed settles to a value, from which future research should show that this is indeed the human force applied, and provides added force in the subsequent amplification phase. The experiment acts as some proof-of-concept for the NFE controller but it is far from being a practical applicable implementation.

For the PAC, unfortunately, no useful functioning at all is achieved. The necessity of a smooth acceleration feedback signal appears to be a significant weakness. Even mounting an acceleration sensor could not provide a proof-of-concept as parasitic high-frequency dynamics in the robotic system still prevented obtaining a smooth signal.

In general the conclusion of this thesis is summarized as follows; Both controllers in theory provide a solution for the problem statement, however, obtaining proper feedback estimates for control calculations needs additional research attention.

6.2 Recommendations

As already concluded in the previous section, the existing controller of [41] and the proposed controller approach of this thesis need additional research to be implementable in practice. To support such research this section provides recommendations for improvements and further research.

The recommendation which should get highest priority for future research is the following. To be able to let the controller approaches succeed, it is a necessity that a solution is found that is able to offer smooth feedback estimate signals (i.e. velocity and acceleration estimates) that are fast enough to track the real velocity and acceleration, including the steps in acceleration at phase transitions, and still maintain a proper reduction of the noise level. This will require extensive additional research. Other recommendations are:

- It was already expected that determining a sufficiently high algorithm cycle frequency should be empirically determined. Experiments have shown that the pulse width modulation nature of both algorithms introduce strongly undesired vibrations into the system when acting at 100 Hz. More experiments should be performed to determine which frequency range is more applicable to avoid the introduction of such undesired vibrations.

- The PAC estimates the mass by applying an adaptation law, which contains a multiplication of a gain $\Gamma$ with a defined error. This error should represent the quality of the mass estimate. However, as shown before, it is affected by an additional term that grows as the enhancement/adaptation phases progresses in time. Furthermore this undesired term gains significance if the mass estimate is approximately equal to the real mass. The term
decreases the trustworthyness of the error regarding the quality of the mass estimate. Two solutions are proposed. The first is making the gain $\Gamma$ phase time dependent. At the start of each new enhancement/adaptation phase the gain should start high and decrease if the time in the phase progresses. The second solution is making the adaptation gain $\Gamma$ error dependent. If the error decreases so should the gain as the error becomes less trustworthy regarding the quality of the mass estimate.

- Making the adaptation gain of the PAC error dependent could also offer another advantageous perspective. If the error is large then the ratio of the error compared to the noise level the error contains, is most beneficial in favor of the error. That is, the error is relatively much less influenced by noise and therefore more representative for the mismatch of the estimated mass.

- Solely for research purposes it might be useful to first perform experiments with a small mass. For the NFE controller the advantage is that much lower feedback gains are required to ensure obtaining a force estimate within the estimation phase. For the PAC the main advantage will be that the achieved accelerations are much higher, which decreases the effect of the noise in the acceleration estimates.

- Finally, it might be worth to choose another experimental setup than the CFT-transposer as used for the experiments of this thesis. Another experimental setup should have good encoder specifications that diminish quantization errors responsible for introducing noise. Furthermore, the experimental setup should not be subject to the parasitic high-frequent dynamics as encountered in the CFT-transposer. Then an acceleration sensor could offer possibilities to deliver a first proof-of-concept for the PAC. It is also recommendable to install a force sensor to be able to directly confirm force estimates that follow from both controller approaches.

If the recommendations above lead to good results, the next step should be extending the problem. Especially the initial assumptions stated in the problem statement should be eliminated for more practical implementations:

- For this thesis the load is regarded as a time-invariant point-mass. It will be interesting to extend this with moments of inertia and supplementary dynamics. Furthermore handling loads from which the mass is time dependent could be interesting. Examples of the latter are paint spraying where the carried paint storage empties or casting liquid metals from a transportable storage in a mold in a foundry.

- For this initial study only one degree of freedom is considered. To make the control algorithms more useful this should be extended to multiple degrees of freedom. The latter also implies that the algorithms should be able to cope with gravitational forces, which obviously is unavoidable in real practical applications.
Appendix A

Simulation results of other human force input signals.

In Section 4.2.2 first simulations of the PAC are shown. This appendix will present additional simulations, covering different cases of human input force, to support first results of Section 4.2.2.

As shown in Section 4.2.2, the estimate of \( m \) and therefore \( \hat{F}_H \) is affected by the type of force applied by the human operator. The signal used in Section 4.2.2 is a sinusoidal one. To show that other force input signals also give satisfactory results, additional simulations are performed. Parameters are chosen identical to those used in Section 4.2.2, so the PAC is set to function at an execution rate of \( f_a = 100\text{Hz} \), the initial estimate of \( \hat{m} \) is set at \( \hat{m}_0 = 60Kg \) with a real mass of \( m = 125Kg \) and \( \Gamma = 1500 \). Furthermore the desired amplification factor is set at \( \alpha = 3 \) and the PAC starts functioning at \( t = 5s \) again.

Figures A.1 and A.2 show the simulation results of a step in the force input while figures A.3 and A.4 show the simulation results for a ramp force input respectively. In both cases, good results are obtained; The mass estimates \( \hat{m} \) converge nicely to the real mass value and therefore so do the human operator force estimates to the real human force.

These additional simulations illustrate that the PAC is able to handle different kind of human force signals in a proper manner.
Figure A.1: Real and estimated human force.

Figure A.2: Mass estimation.

Figure A.3: Real and estimated human force.

Figure A.4: Mass estimation.
Appendix B

Amplitude spectra for several testcases

Because mounting an acceleration sensor on the experimental setup could not provide smooth acceleration signals, the conclusion is drawn that there are parasitic high-frequent dynamics present that prevent a smooth signal.

To be conclusive about this, and to excluded the possibility of interference of the sensor measurement with other signals, the following experiments are performed:

1. sensor in hand, no movement (see Figure B.1),

2. sensor mounted on robot, robot power off, encoders off, no movement by human operator (see Figure B.2),

3. sensor mounted on robot, robot power off, encoders on, no movement by human operator (see Figure B.3),

4. sensor mounted on robot, robot power off, encoders on, with movement by human operator (see Figure B.4),

5. sensor mounted on robot, robot power off, encoders off, with movement by human operator (see Figure 5.7),

6. sensor mounted on robot, robot power on, encoders on, no movement by human operator (see Figure B.6),

7. sensor mounted on robot, robot power on, encoders on, with movement by human operator (see Figure B.7).

Together these experimental results form a complete testcase to support the conclusion that there are indeed parasitic high-frequent dynamics present in the experimental robotic setup at hand. Namely, in the experiments that the robot is moved, regardless of other signals running from and to the robotic setup, the spectra show amplitudes present at higher frequencies. These amplitudes are thus due to the undesired parasitic high-frequent dynamics.
Figure B.1: Amplitude spectrum acceleration sensor measurement, experiment 1.

Figure B.2: Amplitude spectrum acceleration sensor measurement, experiment 2.

Figure B.3: Amplitude spectrum acceleration sensor measurement, experiment 3.

Figure B.4: Amplitude spectrum acceleration sensor measurement, experiment 4.
Figure B.5: Amplitude spectrum acceleration sensor measurement, experiment 5.

Figure B.6: Amplitude spectrum acceleration sensor measurement, experiment 6.

Figure B.7: Amplitude spectrum acceleration sensor measurement, experiment 7.
Bibliography


