Master Thesis

Adaptive human model-based control for active knee prosthetics

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Adaptive Human Model-Based Control for Active Knee Prosthetics

Master Thesis
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October 2014
Abstract

Every unimpaired person in the world walks thousands of steps every day, and has an individual gait pattern, e.g. different velocities, load conditions, surrounding/ground conditions. Unfortunately, the number of lower-limb amputees has been increasing during the last centuries and millions of people are currently affected by amputation. To restore human walking abilities, an active knee prosthesis needs to be seamlessly integrated into the human control-loop. The aim of this thesis is to design a biomimetic adaptive impedance control for active knee prostheses. This controller has to be capable, firstly, of reproducing the physiological impedance modulation of a healthy leg, secondly, of adapting the impedance of the leg depending on its interaction with the environment. To determine essential characteristics of the control-loop, physiological models of human-based control were considered, and design requirements were derived from biology. To design the biomimetic adaptive controller, two different impedance models have been tested, i.e. a spring damper model (BK) and a neuromuscular skeletal model (NMS). Then, a Human Model Reference Adaptive Control (HMRAC) has been tested, with both impedance models, using different High Level Controllers (HLC), i.e. Complementary Limb Motion Estimation (CLME) and Finite State Machine (FSM). The HMRAC modifies the knee impedance depending on the error in position between the actual knee angle and a reference knee angle estimated online from the user via CLME. When the HMRAC is active, the error in position can be minimized to 4.44°, which is below the smallest perceivable error in position for human lower limbs. The torques generated respect the profile and the range of the human physiological torques. Three healthy test subjects reported an improvement in terms of comfort and perception when the HMRAC control with NMS impedance model was used. On one hand, these results show that the NMS impedance model is superior to the BK impedance model if an appropriate set of user-specific impedance parameters is used. On the other hand, the HMRAC is able to modulate the impedance of the leg in a physiological way: the knee torque is changed with the minimum effort to reduce the error in position w.r.t. a desired trajectory estimated from the user intention.
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Acknowledgements
Declaration of Originality

I hereby declare that the written work I have submitted entitled

Adaptive Human Model-Based Control for Active Knee Prosthetics

is original work which I alone have authored and which is written in my own words.¹

Author(s)

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Supervision

Anna Pagel

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Symbols

Symbols

\[ m \quad \text{mass [kg]} \]
\[ g \quad \text{gravitational acceleration [m/s}^2\text{]} \]
\[ \rho \quad \text{density [kg/m}^3\text{]} \]

Acronyms and Abbreviations

- ETH: Swiss Federal Institute of Technology
- SMS: Sensory-Motor Systems Lab
- HMRAC: Human Model Reference Adaptive Controller
- RIC: Rehabilitation Institute of Chicago
- MIT: Massachusetts Institute of Technology
- HLC: High Level Control
- MLC: Medium Level Control
- LLC: Low Level Control
- DVC: Direct Volitional Control
- VC: Volitional Control
- AMR: Activity Mode Recognition
- LDA: Linear Discriminant Analysis
- QDA: Quadratic Discriminant Analysis
- DBN: Dynamic Bayesian Network
- SVM: Support Vectors Machine
- ANN: Artificial Neural Networks
- FSM: Finite State Machine
- DT: Decision Trees
- MMG: Mechanomyography
- IMU: Inertial Measurement Unit
- GRF: Ground Reaction Force
- FSR: Force Sensitive Resistor
- CoP: Center of Pressure
- CoG: Center of Gravity
- CNS: Central Nervous System
- PNS: Peripheral Nervous System
- TF: Transfemoral
- ODE: Ordinary Differential Equation
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<thead>
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<th>Symbol</th>
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<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
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<tr>
<td>FSC</td>
<td>Finite State Controller</td>
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<tr>
<td>CLME</td>
<td>Complementary Limb Motion Estimation</td>
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<td>BW</td>
<td>Bandwidth</td>
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<tr>
<td>CIC</td>
<td>Computational Intrinsic Control</td>
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<td>IEC</td>
<td>Interactive Extrinsic Control</td>
</tr>
<tr>
<td>SEA</td>
<td>Series Elastic Actuator</td>
</tr>
<tr>
<td>SVA</td>
<td>Series Visco-elastic Actuator</td>
</tr>
<tr>
<td>GTO</td>
<td>Golgi Tendon Organ</td>
</tr>
<tr>
<td>MS</td>
<td>Muscle Spindle</td>
</tr>
<tr>
<td>BK</td>
<td>Spring Damper Model</td>
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<tr>
<td>NMS</td>
<td>Neuromuscular Skeletal Model</td>
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<tr>
<td>HAT</td>
<td>Head-Arm-Trunk complex</td>
</tr>
<tr>
<td>PEA</td>
<td>Parallel Elastic Actuation</td>
</tr>
<tr>
<td>SVEA</td>
<td>Series Visco-Elastic Actuation</td>
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<tr>
<td>HLTY</td>
<td>Healthy</td>
</tr>
<tr>
<td>PROS</td>
<td>Prosthesis</td>
</tr>
<tr>
<td>SoA</td>
<td>State-of-the-Art</td>
</tr>
<tr>
<td>GC</td>
<td>Generalized Coordinates</td>
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<tr>
<td>PU</td>
<td>Parametric Uncertainty</td>
</tr>
<tr>
<td>SPPELL</td>
<td>Smallest Perceivable Position Error for Lower Limbs</td>
</tr>
<tr>
<td>SIPE</td>
<td>System Identification and Parameter Estimation</td>
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Chapter 1

Introduction

In 2008, Ziegler-Graham et al. published an article in the Archives of Physical Medicine and Rehabilitation that provided current estimates of limb loss in the United States, along with projections of limb loss rates through the year 2050 [114]. Starting with work from 1996 claiming an amputation rate of approximately 185,000 persons per year and a total of 1.2 million persons living with limb loss [2], Ziegler-Graham et al. constructed a probabilistic model that accounts for new incidents of limb loss and mortality. From this model, it was estimated that 1.6 million persons were living in the United States with limb loss in 2005, and, by 2050, this number will more than double. According to Sup at al. [88], there are currently more than 300,000 transfemoral amputees in the United States and there is an estimate of around 7 million transfemoral amputees worldwide. Approximating Ziegler-Graham model for the world population, claiming that there are currently 7 million transfemoral amputees worldwide, one would expect around 14 million amputees by 2050. Thus, the need of development of lower limb prosthetic devices is becoming essential for the humanity.

1.1 State of the Art in Hardware and Control

Traditionally, lower limb prostheses were passive by necessity; indeed, the technology required to construct a powered device comparable in size and weight to the anatomical limb has only been developed in the last ten to twenty years. The first steps towards powered prosthetics were realized with the Belgrade transfemoral prosthesis in the late 1980s [78]. Compared to passive prostheses, energy consumption of amputees was reduced and maximum walking speed was increased for the first time. A couple of decades later, only a few systems are able to generate energy and create torques actively in the knee and/or ankle joints. The majority of these systems originates from research institutions (check Tab. A.1); only four devices are commercially available.

The first commercialized active foot was the Proprio Foot (Ossur, [68]). The powered foot-ankle prosthesis is equipped with accelerometers and angular sensors to detect the current state of the device and the most appropriate gait mode: level ground walking, stair climbing, sitting and relaxed. Based on the state of the device, a linear actuator drives the ankle during swing phase, i.e. it has the possibility to lift the toe to adapt to the terrain and to prevent from trips or falling. The second device was the Power Foot, an active ankle-foot prosthesis developed later by BiOM [10], a start-up grew out of a research effort led by Dr. Hugh Herr at MIT. This prosthetic ankle allows not only swing phase adaptation but also active push-off, which has been proven to be fundamental to achieve natural, i.e. almost unimpaired, and efficient gait, i.e. with low metabolic consumption [6, 29]. Powered ankle joints for walking and running were also developed at Springactive (SPARKy, [85]) and Westpoint Military Academy [40] based on a design from
Arizona State University.

The first commercialized active knee prosthesis was Ossur’s Power Knee (Ossur, [68]). The device was presented to the market in 2006 and a new version was released in 2011. An actuator provides positive work during ascending stairs and slopes, standing up and walking, and is able to dissipate energy during stairs and slopes descent. The motor lifts the heel for swing flexion and to accommodate the foot at heel strike. As in the BiOM foot, a Series Elastic Actuator (SEA) is storing energy during stance phase flexion and releases it later to assist the motor. Martinez-Villalpando et al. showed that a similar device, i.e. active knee joint with antagonistic SEA element, can increase amputee’s walking speed up to 17% from 1.12 to 1.31 m/s compared to the C-Leg (Ottobock, [69]), and still reduces the metabolic cost by 6.8% [64].

At the Vanderbilt University, a powered knee and ankle prosthesis was developed [87]. The control of the prosthesis, called the Vanderbilt Leg, was further investigated and improved for several years at the Rehabilitation Institute of Chicago (RIC) to achieve good control performance during level ground walking, stair and slope climbing/descending, standing, sitting and, finally, running [83]. The leg will be further improved and commercialized by Freedom Innovations [49].

During the last decades, notions of control have also been continuously expanding from the traditional closed loop-control concept to include different functionalities such as coordination, situation awareness, intention estimation and planning. According to Grimmer et al., the control of a prosthetic device can be classified in Computational Intrinsic Control (CIC) and Interactive Extrinsic Control (IEC) depending on the kind of interaction between the user and the prosthetic device. CIC has no direct connection to the user while IEC is based on a direct communication between brain and device that can be realized either in the efferent command or in the afferent feedback signal (see Fig. 1.1). An important advantage of IEC w.r.t CIC is that it allows the triggering of a specific activity before a perceivable motion is executed, while CIC can only act after a motion already occurred. In particular, the major control strategies used for control of active prosthesis include:

- **Muscle Reflex Control** is a kind of CIC that uses mechanical sensors to replace/emulate the missing Muscle Spindle (MS) and Golgi Tendon Organ (GTO) sensory feedback. On one hand, the sensor information is used as input for a force and length (e.g. muscle stretch) feedback controller. On the other hand, the sensors detect the gait phase and transitions to set a state machine, i.e. stance or swing phase. Eilenberg et al. transferred this control concept to the Power Foot [20].

- **Finite State Machine (FSM) Impedance Control**, also known as State Machine control,
is by far the most common CIC strategy used around the world. Electro-mechanical sensory information from the device can be used with an appropriate set of classifiers, to detect the desired gait mode (e.g. walking, stair climbing, etc.) or to separate different phases of the gait cycle. Each of the states in which the gait cycle is divided, is specified by constraints on knee joint kinematics and is associated to a set of constant impedance parameters. Once the controller enters a specific state, the impedance model’s parameters are modified according to the new state’s set of parameters. In particular, the impedance model is chosen to match human reference joint torque and position trajectories. The transitions between states are defined by parametric laws that are heuristically chosen based on a prototypical gait cycle. The FSM has been implemented by many different groups and with a wide variety of devices, i.e. Varol, Fite, Goldfarb et al. apply it to the Vanderbilt leg at RIC [23, 57–59, 88, 98], Goršič et al. apply it to the CYBERLEGs ankle-knee prosthesis [28], Hoover et al. to the prosthetic knee at Clarkson University [45], Liu et al. to the Kanazawa’s ankle prosthesis [62]. At ETH Zurich, Pfeifer et al. implemented for the first time on the ANGELAA knee exoprosthesis a FSM impedance control for level ground walking and stair ascent/descent [71]. As shown in Fig. 1.2, the FSM divides the gait cycles in four states, each associated to a set of constant knee impedance parameters.

![Figure 1.2: State Machine-based variable impedance control as implemented by Serge Pfeifer in his PhD Thesis [71]. Impedance modeled as a spring damper system.](image)

- **Phase Plane Control** is also a kind of CIC in which the desired system state, called invariant trajectory i.e. position and velocity, is expressed as a function of gait phase and stride length. For instance, in the prosthetic ankle developed by Holgate et al. [43], a gyro sensor is used to measure shank angular velocity and position w.r.t. the ground, and from it a phase plot is generated (see Fig. 1.3). The phase plot represents the direct relation between the current shank angular position and velocity and the desired gait phase and step length/velocity, also called invariant trajectory. Gregg et al. apply this control to the Vanderbilt leg at RIC and state that the relation found in the phase plot can be considered independent of time, gait speed and ideally subject [30]. Indeed, the biggest advantage of this control strategy is the possibility of automatic speed or step length adaptation during the gait cycle.

- **Echo Control** is a kind of CIC in which the joint trajectories of the sound limb are recorded and repeated in the impaired leg with a specific time delay and, if necessary, scaling/modification. Despite evident limitations of this kind of control with asymmetric activities or gait cycles with an odd number of steps, the Echo control is still in use nowadays by Wang et al. [101].

- **Complementary Limb Motion Estimation (CLME) controller** is a CIC that infers the intended motion of impaired limbs from residual body motion [74, 96] and maps this information to either a reference trajectory (if a position control is used, [96]) or to the stiff-
Chapter 1. Introduction

Figure 1.3: Phase plane trajectories of shank velocity and shank angle for walking and running. Polar angle $\phi$ is used for gait percent determination. Polar radius $r$ used for speed determination. Touch down is visualized by a cross, take off by a circle for each speed.

ness/setpoints of an impedance model (if an impedance/admittance control is used, [75]). The CLME controller needs to be trained offline using physiological gait data from different healthy subjects. Using these data, a mapping, called contralateral mapping $\Gamma$ (see Fig. 1.4), is statistically regressed between residual limbs motion (e.g., $x_{\text{imu}}$) and impaired leg motion (e.g., trajectory $\theta_{\text{rot}}$ and impedance parameters). A set of goniometer/gyroscopes or IMUs is commonly used to sense the complementary limbs/joints dynamics. Using offline analysis, it is possible to determine which is the most appropriate set of predictors (sensory inputs set) that can be used to estimate the intended device state. In general, the most suitable predictor set is based on the kinematics of sound thigh and shank. The contralateral mapping has some limitations. First, the inter-subject differences in gait patterns make the choice of a suitable training subject very challenging. Second, a different contralateral mapping has to be trained for each possible gait mode. Third, the changes in dynamics due to the user’s impairment and prosthetic device are not considered. For these reasons, the CLME control is often not able to reproduce either the trained healthy gait pattern or the amputee’s gait pattern in the prosthetic device. It is a common mistake to confound CLME with echo control because both of them are based on information recorded from complementary limbs (e.g. sound leg). Instead, CLME and Echo Control are very different because CLME complements residual body motion without time delay, it is a continuous control, i.e. not related to the concept of gait phase, and it does not require a change in control strategy between stance and swing phase.

- **EMG Based Control** is the most common IEC strategy and it can be used in two different ways: as a Direct Volitional Control (DVC) or as an Activity Mode Recognition (AMR). DVC allows the user to directly control the device’s state, i.e. joint position, velocity and torque. It is fundamental in conditions in which the locomotive task is irregular and non-periodic (e.g. queueing, waiting, walking on uneven terrains) or during non-weight bearing activities (e.g. leg voluntary repositioning) as implemented by Goldfarb et al. on the Vanderbilt leg [35]. AMR is able to distinguish and switch between different gait modes thanks to their cyclic nature. In order to classify the gait modes, pattern recognition techniques and classifiers are commonly used. The inputs to the classifier, in general, include sensory informations coming from the user, the environment and the device. Two possible classifiers can be used: automated pattern recognition and heuristic rule-based classifiers. In the first method, the classifier is trained on a set of EMG data and automatically establishes specific classification decision boundaries. Hargrove and Goldfarb et al. applied this method to the Vanderbilt leg respectively at RIC [39,108,113] and at the Vanderbilt University [27]. In the second method,
1.1. State of the Art in Hardware and Control

Figure 1.4: Contralateral mapping for the online estimation of the desired prosthetic state. The mapping $\Gamma$ is trained offline using healthy gait data and it relates the motion of one limb ($\theta_{\text{ref}}$) to the motion of its complementary limbs, i.e., sound leg, which can be measured with goniometer/gyroscopes or IMUs ($x_{\text{IMU}}$). The contralateral mapping is then used, in an impaired subject, to map the motion of a complementary limb (e.g., sound leg) to the motion (e.g., impedance parameters and/or trajectory $\theta_{\text{ref}}$) of the prosthetic device.

The designer specifies a set of heuristic rules that indicate the transition from one gait mode to another, often using FSMs. This method has been used by Varol et al. on the Vanderbilt leg [89], by Gorišč et al. on a new active knee-ankle prosthesis (project CYBERLEGS, [28]) and by Sun et al. on an active ankle prosthesis at Marquette University [86].

- **Neuromuscular Mechanical Fusion** is based on the synchronous use of EMG (IEC) and electromechanical sensors signals (CIC). This control can be used either for DVC or AMR as the EMG control, but allows a more robust and reliable pattern recognition. One possible technique include the use of EMG signals, combined with the Ground Reaction Forces (GRFs) and torque measurements coming from a load cell on the prosthetic pylon. Huang et al. was the first group to try this approach in 2011 and they showed that neuromuscular-mechanical fusion outperforms methods that use only EMG or mechanical information [47]. This work has been further improved over the years by Young et al. [107] introducing new kinds of classifiers. Delis et al. from University of Brasilia implemented another possible technique using EMG signals combined with gyro sensors’ data [17].

It is important to underline that the first three control strategies are based purely on electromechanical sensory information coming from the prosthetic device. This represents an appealing solution to estimate the device’s state because the sensors are fully embedded in the prosthesis and do not need to be worn separately. Indeed, this is the major advantage of the Power Knee from Ossur [68] compared to other existing devices still under research. On the other hand, even though the other approaches are sometimes more bulky and less practical for everyday use, they reduce the control delay because they allow for a more direct intention estimation.
1.2 Objectives

Although recent developments both in active prosthetics hardware and control allow for direct (IEC) and/or indirect (CIC) user-cooperative controllers (Sec. 1.1), these kind of controllers have still some limitations. On one hand, they do not necessarily guarantee a physiological impedance modulation in the leg, thus, the user is not able to move and feel the prosthetic device as its own leg. On the other hand, they are not flexible and they completely miss the ability to adapt, which is one of the fundamental characteristics of human motion control. Indeed, humans are able through reflexive mechanisms, to subconsciously adapt both to unexpected perturbations and to uncertainties coming either from the environment or their own body, i.e. changes in body dynamics and physical characteristics. On the opposite, the existing user-cooperative controllers often burden the user with a high cognitive load, because the user has to constantly concentrate on his movements during the interaction with the environment. To reproduce biomimetically the behaviour of a healthy limb in a prosthetic limb, this master thesis has two main objectives:

1. Reproduce in a active prosthetic leg the physiological impedance modulation of a healthy human leg during level ground walking.
2. Design an adaptive impedance control that is able to modulate biomimetically the knee impedance to react to perturbations and uncertainties.

To achieve the first goal, two different impedance models, i.e. a spring damper model (BK) and a Neuromuscular Skeletal model (NMS), are tested using two different CIC impedance controllers. The first impedance control is based on CLME, while the second is based on a FSM control. To achieve the second goal, a bio-inspired Human Model Reference Adaptive Controller (HM-RAC) is added in parallel to the impedance controllers mentioned above to correct the impedance modulation in the prosthetic leg. In particular, the adaptation of the impedance depends on the position error of the actual knee trajectory w.r.t. a desired physiological trajectory. To find out which impedance controller allows for a better impedance modulation and maximal user-cooperativeness, all the possible controllers, i.e. FSM or CLME with/without HMRAC, based on different impedance models, i.e. BK or NMS, have been tested with three healthy subjects, as described by the schematic in Fig. 3.10.

1.3 Outline

This thesis is organized as follows:

Chapter 2 presents the most important biological aspects that have been considered to design an impedance controller inspired by nature. In particular, the chapter describes state-of-the-art (SoA) engineering tools that are able to reproduce or model fundamental characteristics of human locomotion. First, a general control architecture for active prosthetics is compared to the motion control in the human body. Second, the two SoA BK and NMS impedance models are presented. Third, biomechanical models of the human body during level ground walking are introduced. Fourth, a novel scaling between the impedance of a human leg and the impedance of a knee exoprosthesis is presented. Finally, the active exoprosthesis ANGELAA used for tests is presented.

Chapter 3 presents the design of the different impedance controllers tested. In the first section, a basic FSM impedance control based on the NMS or the BK impedance models is designed and tested in order to verify the performance of the two impedance models. In the second section, a HMRAC controller is designed and tested. This controller is tested in parallel
either with a FMS or with a CLME impedance controller, which is based on a NMS or on a BK impedance model. In each of the two sections, the protocols used for the respective experiments with healthy subjects are presented.

Chapter 4 presents the results of the simulations and experiments presented in the two sections of Chapter 3.

Chapter 5 presents the discussion of the results of the simulations and experiments reported in Chapter 4.

Chapter 6 summarizes the contributions and conclusions of this thesis. Suggestions for future work are outlined at the end of Chapter 6.

Appendix A presents a detailed SoA about the hardware and control strategies for active lower limb devices around the world.

Appendix B presents details about biomechanic dynamic models used throughout the thesis for impedance scaling derivation, control design and simulations.

Appendix C lists where the Matlab codes and experimental data used during the thesis can be found in the Master’s Thesis CD.
Chapter 2

Learning from Nature

Nature can be often considered as the most inspiring control book, especially in problems that concern the reproduction of natural phenomena or the interaction with humans. Thus, it is important to check if and how it is possible to reproduce natural behaviours and control mechanisms using engineering tools. First, this chapter starts presenting similarities between a generalized control structure used for active prosthetics and the human motor control system. Second, two different impedance models mimicking the impedance modulation in human joints are presented. Third, a four segmented biomechanical model of the human body is introduced. This model will be used as basic model for subsequent control design and simulation. Fourth, a mathematical scaling between the impedance profile of a healthy leg and of a prosthetic leg is presented. Finally, the hardware of the prosthetic leg ANGELAA, used as test platform for this thesis, is presented. This prosthetic leg has been designed at the SMS Lab, ETH, to biomimetically replicate the kinematics and impedance of a healthy leg.

2.1 Human Motion Control versus Prosthetic Control

In the world of active lower limb prosthetics, it is generally possible to schematize the various control strategies with a generalized architecture. This generalized structure is based on the well known hierarchical control architecture [105] that is widely used in various highly complex systems, i.e. processing plants, manufacturing processes, aerospace vehicles [34], and biomedical and human-robot interactive devices [19]. A typical hierarchical control architecture is depicted in Fig. 2.1 (modified from [98]). The major scheme includes the user wearing the prosthesis, the hierarchical control and the surrounding environment. Each of the subsystems is connected to the others via direct physical or signal interaction. A basic scheme of the human motor control is represented in Figure 2.2.

Comparing Fig. 2.1 and Fig. 2.2, it can be observed that both in the human body and in active prosthetics the hierarchical motion control scheme can be divided in:

- **High Level Control** (HLC) - green. In prosthetics, the HLC determines the user’s locomotive intent and it is responsible for user-cooperativeness, which represent the ability of the prosthetic device to cooperate with the user to realize his desired motion. The HLC communicates the user intention to the mid and low level control which are responsible for the actuation of the user intention in the physical device. Similarly, in the human body, the Central Nervous System (CNS) is responsible for motor planning and motor control. The
Figure 2.1: General hierarchical control scheme for powered lower limb prostheses. The control scheme is made of three layers: High Level Control (green) responsible for intention estimation and user cooperation; Mid Level Control (blue) responsible for conversion between intention and execution; and Low Level Control (violet) responsible for actuation and execution. The control scheme is designed to facilitate a seamless transition between different levels of control based on the user's intent and environmental feedback.
CNS communicates the motor plan through the spinal cord to the rest of the body, which is responsible for the generation of the desired motion.

- **Mid Level Control** (MLC) - blue. The MLC receives the information from the HLC and converts it from the estimated locomotive intent to a desired device state for the low level controller to track. The locomotive intent coming from the HLC is usually defined using a set of parameters (e.g. impedance parameters) and the desired state for the device is sent to the low level control as either a torque or position/velocity, depending on the kind of control used. The conversion is often operated using a specific constant or adaptive model (e.g. an impedance model). Multiple MLC can be present to accommodate different activity modes. Similarly, humans convert the nervous signals coming from the CNS, through the spinal cord, into a motor command (afferent feedback) that is sent to the muscles. The motoneurons, responsible for transporting motor commands to the muscles to be executed, convert the efferent excitation signal into a muscle activation signal. In parallel, the limb sends back torque/kinematic feedback to the spinal cord via afferent feedback.

- **Low Level Control** (LLC) - purple. The purpose of the low level control is to calculate the error between the current and the desired state of the device computed in the MLC, and act to minimize this error. In the human body, the LLC is executed by the muscles, which are responsible for the generation of the limb's force.

A controller does not necessarily include all the three layers. The MLC may be missing or may be included within the HLC. The control strategies proposed in the introduction are classified depending on their HLC strategy, and they can be applied using different MLC models (e.g., trajectory, impedance, etc.) and, accordingly, appropriate LLC.

As mentioned in the introduction, standard impedance controllers are able to replicate the behavior of a human leg only under restricted conditions. Often, they miss the capacity to restore the versatility and adaptability of a human leg during interactions with the environment. To replicate the physiological modulation and adaptation of the leg impedance, a bioinspired impedance controller should be able to adapt the impedance of the prosthetic limb following the same rules that are used in the human body. According to Ganesh et al. [24], the impedance of a human leg is adjusted using the following principles:

- The human leg impedance is modified to minimize the error of the actual movement w.r.t. a desired movement decided by the HLC. The reflexes, i.e. afferent feedback and efferent reaction to unexpected changes, are responsible for impedance modulation. These subconscious mechanisms are always active and they can be used while reacting to perturbations and interactions with the environment.

- The modification of the leg impedance is a tradeoff between minimization of trajectory error and minimization of the actuation effort. To save energy, the leg impedance has to be modified as little as possible to guarantee a correct movement.

A biomimetic adaptive controller can be used to best replicate and replace human subconscious reflexive mechanisms. In particular, it is important to keep in mind that the adaptive control aims to replace only the reflexes that are missing from the prosthetic limb. At the same time, the control is cooperating with the human body that is also adapting in parallel to the behavior of the prosthetic leg and to the environment.
Chapter 2. Learning from Nature

2.2 Impedance Models

To implement an impedance control, an appropriate impedance model is required. In general, the impedance models are used in the MLC to convert the user intention estimated in the HLC, into a desired state for the prosthetic device, controlled by the LLC. The better the model, the better will be the controller performance and the behaviour of the robotic limb compared to the corresponding human limb. In this thesis, two different models have been implemented: a spring damper model, also known as BK model, and a Neuromuscular Skeletal (NMS) model.

The BK model is defined by Eq. (2.1):

$$\tau_{mdl}(t) = k(\theta_k(t) - \theta_0(t)) + b\dot{\theta}_k(t).$$  \hspace{1cm} (2.1)

The model is made of two linear components: A spring component with stiffness $k$ and setpoint $\theta_0$, and a damper with damping coefficient $b$. The desired impedance state of the device is defined by
2.3 Biomechanical Models of the Human Body

During this thesis, biomechanical models of the human body will be necessary. They will be used for theoretical evaluation of the unimpaired and impaired impedance profiles of the knee joint, for Matlab simulations of the leg dynamics, and for the implementation of an adaptive control for active prosthetics. In this section, the inverse dynamics of a four segmented model of an unimpaired subject during stance phase is presented. All the other models that will be used are very similar to the model presented here, thus they will not be discussed in this section but their extensive derivation and Matlab code can be found respectively in Appendix B and Appendix C. Table 2.1 gives more details about the different models used in this thesis, their structure and purpose, and the sections in which they have been used.

the set of impedance parameters \([k, b, \theta_0]\) and it is commanded to the LLC as desired model torque \(\tau_{mdl}\). In an impedance control scheme, the impedance parameters are computed in the HLC.

The NMS model is defined by Eq. (2.2):

\[
\tau_{int}(t) = k_i(\theta_k(t) - \theta_0(t)) + b_i \dot{\theta}_k(t)
\]

\[
\tau_{ref}(t) = [k_{ms}(\theta_k(t-T) - \theta_0(t-T)) + b_{ms}\dot{\theta}_k(t-T) + k_{gto}\tau_k(t-T)]H_{act}(t)
\]

\[
\tau_{mdl}(t) = \tau_{int}(t) + \tau_{ref}(t).
\] (2.2)

The model is based on the work of de Vlugt et al. at TU Delft [16] and it consists of two distinct components: An intrinsic component \(\tau_{int}\) and a reflexive component \(\tau_{ref}\). The intrinsic impedance component represents the intrinsic properties of muscles, tendons and surrounding tissues. It can also be described by a spring \(k_i\), a setpoint angle \(\theta_0\) and a damping \(b_i\). The reflexive impedance component represents the activation-dependent muscle properties that are related to afferent feedback. Afferent feedback originates from sensory signals from Muscle Spindles (MS) and Golgi Tendon Organs (GTO). MS can be modeled as a spring-damper system with \(k_{ms}, \theta_0\) and \(b_{ms}\). The GTO provides feedback about the joint torque and is thus represented by the gain \(k_{gto}\). The sensory information about joint position/velocity and torque has a delay \(T = 40\text{ms}\) that represents the delay in the sensory afferent feedbacks present in the human body. The output of the reflexive component represents the efferent excitation signal that is commanded from the spinal cord through the motoneurons as a response to the afferent feedback coming from MS and GTO.

An Excitation to Activation transfer function \((H_{act})\) converts the excitation signal into a desired knee torque. This corresponds, in the human body, to the activation of the muscles in response to the reflexive arc. The excitation to activation conversion is implemented, according to de Vlugt et al. [16,97], using a second order dynamical system with natural frequency \(\omega_n = 2.2\text{Hz}\) and relative damping \(\beta = 0.7\). The sum of reflexive torque \(\tau_{ref}\) and intrinsic torque \(\tau_{int}\) defines the desired impedance state of the prosthetic device, commanded as desired model torque \(\tau_{mdl}\).

To identify the profiles of the impedance parameters of both models, two different methods can be used: model-based estimation and experiment-based estimation. In the case of the BK model, Pfeifer et al. used a model-based impedance estimation to determine the stiffness profile of a healthy knee joint during the gait cycle. In particular, as shown in Fig. 2.3, a set of healthy gait data during level ground walking including GRFs, kinematics and EMG signals was recorded and a human model was used to estimate the profile of the knee stiffness during the stride [73]. In the NMS model, System Identification and Parameter Estimation (SIPE) experiments are ongoing at TU Delft using an experiment-based approach. The gait data needed for the estimation is recorded using perturbation experiments run on a healthy subject walking on the treadmill (see Fig. 2.4). Currently, the NMS parameters can be estimated only during stance phase. Still, this is sufficient because stance is the most critical gait phase both in terms of user perception and in terms of gait dynamics due to the interaction between the leg and the ground.
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Figure 2.3: Model-based stiffness estimation used by Pfeifer et al. [73].

As shown in Fig. 2.5, the human leg and upper body can be modeled with four segments representing the foot, shank, thigh and Head-Arms-Trunk (HAT). The segments are connected by three hinge joints representing ankle, knee and hip. Mass, inertia, Center of Mass (CoM) and length of each segment are defined using anthropometric data [106]. The model is restricted to two dimensions, i.e. to the sagittal plane. The segment angles are defined w.r.t. the vertical axis, and positive angles are counted counter clockwise. The Newton-Euler method is used to derive the Equations of Motion (EoMs) for the stance phase during a nominal gait cycle. Inverse dynamics are used to compute joint forces and torques based on a set of nominal gait data, i.e. kinematics of the segments, GRFs, and Center of Pressure (CoP) position. Assume CoP position \((x_P, y_P)\), ankle position \((x_A, y_A)\) and segment angles, i.e. \((\theta_f, \theta_s, \theta_t, \theta_{hat})\), to be a set of generalized coordinates (GC) known from gait data w.r.t. a world coordinate system positioned on the ground.
<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Scope</th>
<th>Reference Section</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Segmented model" /></td>
<td>Four segmented model of healthy subject in stance phase. Ankle, knee and hip joint actively torque controlled.</td>
<td>Impedance scaling and inverse dynamics using healthy gait data.</td>
<td>Introduction and implementation: Sec. 2.3. Results: Sec. 2.4. Matlab code: C.1.2.1.</td>
</tr>
<tr>
<td><img src="image" alt="Segmented model" /></td>
<td>Three segmented model of impaired subject in stance phase using a transfemoral prosthesis. Knee and hip joint actively torque controlled.</td>
<td>Impedance scaling.</td>
<td>Introduction: Sec. 2.4. Implementation: Appendix B.1. Results: Sec. 2.4. Matlab code: C.1.2.2 - C.1.2.4.</td>
</tr>
<tr>
<td><img src="image" alt="Segmented model" /></td>
<td>Impaired subject walking during stance phase. Double inverted pendulum with HAT mass. Knee joint actively torque controlled.</td>
<td>Model reference for HM-RAC, stance phase. Additionally, model used to check the adaptive control in a Matlab simulation.</td>
<td>Introduction: Sec. 3.2.1. Implementation: Appendix B.2.1. Results simulation: Sec. 4.2.1. Results control: Sec. 4.2.2. Matlab code: C.1.3.1 and C.1.4.2.</td>
</tr>
<tr>
<td><img src="image" alt="Segmented model" /></td>
<td>Impaired subject walking during swing phase. Double pendulum. Knee joint actively torque controlled.</td>
<td>Model reference for HM-RAC, swing phase</td>
<td>Introduction: Sec. 3.2.1. Implementation: Appendix B.2.2. Results control: Sec. 4.2.2. Matlab code: C.1.3.2.</td>
</tr>
<tr>
<td><img src="image" alt="Segmented model" /></td>
<td>Healthy subject walking during stance phase. Double inverted pendulum. Hip joint controlled by replayed healthy hip forces and torque. Knee and ankle joint controlled by NMS impedance model.</td>
<td>Model used to check the stability/behaviour of the NMS impedance model when controlling a human leg.</td>
<td>Introduction: Sec. 3.1.1. Results simulation: Sec. 4.1.1. Matlab code: C.1.4.1.</td>
</tr>
</tbody>
</table>

Table 2.1: Segmented models used in the thesis to represent healthy/impaired humans during level ground walking.
Figure 2.5: Free body diagrams of a four-segmented model of healthy subject walking during stance phase: a. HAT, b. thigh, c. shank, d. foot.
2.3. Biomechanical Models of the Human Body

Firstly, we can express the CoM of each segment in generalized coordinates:

\[ x_f = x_A - (d_f - l_f) \sin \theta_f \]
\[ y_f = y_A + (d_f - l_f) \cos \theta_f \]
\[ x_s = x_A - d_s \sin \theta_s \]
\[ y_s = y_A + d_s \cos \theta_s \]
\[ x_t = x_A - d_t \sin \theta_t - l_s \sin \theta_s \]
\[ y_t = y_A + d_t \cos \theta_t + l_s \cos \theta_s \]
\[ x_{\text{hat}} = x_A - d_{\text{hat}} \sin \theta_{\text{hat}} - l_t \sin \theta_t - l_s \sin \theta_s \]
\[ y_{\text{hat}} = y_A + d_{\text{hat}} \cos \theta_{\text{hat}} + l_t \cos \theta_t + l_s \cos \theta_s \] (2.3)

and the same can be done for the knee and hip joints.

\[ x_K = x_A - l_s \sin \theta_s \]
\[ y_K = y_A + l_s \cos \theta_s \]
\[ x_H = x_A - l_t \sin \theta_t - l_s \sin \theta_s \]
\[ y_H = y_A + l_t \cos \theta_t + l_s \cos \theta_s \] (2.4)

Secondly, Newton-Euler equations are written for each segment, according to the free body diagrams in Fig. 2.5, along x, y, and around the CoM:

**Foot:**

\[ F_{x_A} + F_{x_P} - m_f \ddot{x}_f = 0, \]
\[ F_{y_A} + F_{y_P} - m_f (\dot{y}_f + g) = 0, \] (2.5)
\[ \tau_A - l_f \ddot{\theta}_f - (x_f - x_P) F_{y_P} + (y_f - y_P) F_{x_P} - (x_f - x_A) F_{y_A} + (y_f - y_A) F_{x_A} = 0. \] (2.6)

**Shank:**

\[ F_{x_K} - F_{x_A} - m_s \ddot{x}_s = 0, \]
\[ F_{y_K} - F_{y_A} - m_s (\dot{y}_s + g) = 0, \] (2.7)
\[ \tau_K - \tau_A - l_s \ddot{\theta}_s + (x_s - x_A) F_{y_A} + (y_s - y_A) F_{x_A} + (x_K - x_s) F_{y_K} - (y_K - y_s) F_{x_K} = 0. \] (2.8)

**Thigh:**

\[ F_{x_H} - F_{x_K} - m_t \ddot{x}_t = 0, \]
\[ F_{y_H} - F_{y_K} - m_t (\dot{y}_t + g) = 0, \] (2.9)
\[ \tau_H - \tau_K - l_t \ddot{\theta}_t + (x_t - x_K) F_{y_K} - (y_t - y_K) F_{x_K} + (x_H - x_t) F_{y_H} - (y_H - y_t) F_{x_H} = 0. \] (2.10)

**Hat:**

\[ - F_{x_H} - m_{\text{hat}} \ddot{x}_{\text{hat}} = 0, \]
\[ - F_{y_H} - m_{\text{hat}} (\dot{y}_{\text{hat}} + g) = 0, \] (2.11)
\[ - \tau_H - I_{\text{hat}} \ddot{\theta}_{\text{hat}} + (x_{\text{hat}} - x_H) F_{y_H} - (y_{\text{hat}} - y_H) F_{x_H} = 0. \] (2.12)
Finally, joint forces and torques at the ankle, i.e. $F_{xA}$, $F_{yA}$ and $\tau_A$, the knee, i.e. $F_{xK}$, $F_{yK}$ and $\tau_K$, and the hip joints, i.e. $F_{xH}$, $F_{yH}$ and $\tau_H$, are computed solving the equations above. Their solution can be found in the Matlab code C.1.1.1.

2.4 Impedance Scaling: From Human to Prosthetic Leg

The impedance models used for impedance control are based purely on analysis of healthy human gait data. But comparing a healthy sound leg and an active knee prosthesis, some mechanical differences are evident:

- The legs have different mechanical properties, i.e. mass, inertia, dimensions.
- A prosthetic foot is different from a human foot in terms of shape, structure and materials. Thus, they lead to a completely different interaction between the user and the environment. Moreover, both human and prosthetic feet can vary a lot one among different people, or different devices, so they cannot be easily modeled or compared.
- There is no actuated ankle joint in the prosthetic leg. Thus, no ankle power is generated.

Therefore, if the same knee torque model is applied in the prosthetic leg and in the sound leg, a different motion and thus a different impedance are obtained, because the different dynamics of two systems are not considered or compensated in any way. To reproduce the same impedance - in a specific kinematic configuration - it is necessary to quantify how the joint torques/forces should be scaled to compensate for the dynamics of the different legs. To identify this scaling, two models of a sound and a prosthetic leg during stance phase have been implemented. In the unimpaired case, presented in Sec. 2.3, the human body is modelled as a four-segmented system, see Fig. 2.5. In the impaired case with prosthesis, discussed in Appendix B.1, the human body is modeled as a three-segmented system, see Fig. B.1. The Newton-Euler method is used to derive the EoMs. To guarantee the same impedance profile, the dynamics of the three-segmented model have been constrained with the following assumptions on their kinematics and forces/torques:

- **Kinematic assumptions.** The prosthetic leg moves with the same hip, thigh/stump and ankle trajectories as the healthy leg. In this way, the body is moving in the same way and maximum foot clearance is guaranteed. Additionally, the same CoP trajectory is required to guarantee the same interaction between user and environment.

- **Forces/Torques assumptions.** The interaction forces with the upper body, i.e. hip forces, ideally have to be the same in the healthy and in the prosthetic leg. This avoids overstress of the hip and guarantees the same interface between upper and lower body. The hip torque cannot be assumed to be the same due to the differences in mechanical properties of the limbs and to not overconstrain the system.

Using the above mentioned constraints, the inverse dynamics of the prosthetic leg model are computed. In particular, the knee and hip torques of the model result to have the structure presented in Eq. 2.17, which represent a mathematical scaling between the joint torques in the healthy leg and the joint torques in the prosthetic leg:

$$
\tau_K = b_K(q) \tau_K + c_K(q)
$$

$$
\tau_H = a_H(q) \tau_A + b_H(q) \tau_K + c_H(q)
$$

(2.17)
where $\tau_K$ and $\tau_A$ are the knee and ankle torques generated in the healthy leg during stance phase, $\tau_Kp$ and $\tau_Hp$ the knee and hip torques of the impaired leg with a knee exoprosthesis, and all the other parameters (e.g., $b_K$, $c_K$, $a_H$, $b_H$, $c_H$) are dependent on the vector $\mathbf{q}$

$$
\mathbf{q} = [m_i, I_i, l_i, \theta_i, \dot{\theta}_i, \ddot{\theta}_i, g, x_A, y_A, x_P, y_P],
$$

which is defined by the mechanical properties (e.g., mass $m_i$, inertia $I_i$, length $l_i$, CoM position $d_i$) and instantaneous kinematics (e.g., position $\theta_i$, velocity $\dot{\theta}_i$, acceleration $\ddot{\theta}_i$) of the segments $i$ of the healthy and/or prosthetic leg, and by the position of ankle and CoP of the healthy leg (e.g., $x_A$, $y_A$, $x_P$, $y_P$). More details about the mathematical derivation and the exact formulation of the scaling can be found in Appendix B.1 and Matlab code C.1.2.1 - C.1.2.4.

The scaling (2.17) shows that using the assumptions mentioned above, an active knee prosthesis is able to reproduce a similar impedance and a similar movement of a unimpaired leg compensating the missing ankle power at the hip joint. Indeed, the knee torque $\tau_Kp$ generated by the prosthesis does not account for the missing healthy ankle torque $\tau_A$, but only for the healthy knee torque $\tau_K$. On the contrary, the hip torque of an impaired user $\tau_Hp$ is a function of both the missing healthy ankle and knee torques. Therefore, the mathematical scaling confirms what already known from medical studies: an impaired user, walking with a active knee prosthesis, overstresses his hip joint and develops compensatory movements because this kind of prosthesis is unable to compensate for the missing ankle power, fundamental in specific phases of the gait cycle, i.e. push off. Thus, the user has to generate the missing ankle power completely at the hip joint. Figure 2.6 and Fig. 2.7 plot the comparison between the hip and knee torques and GRFs of a healthy person and the torques and GRFs of the same person walking with a prosthetic leg of the same size of ANGELAA (details in Matlab code C.1.2.4). From the figures, it is clearly visible that both the knee torque and the GRFs decrease when a prosthetic leg is used. This happens because the prosthetic leg and its socket have on average a smaller mass and inertia compared to a healthy limb. On the opposite, the impaired hip torque is higher than a healthy hip torque because it has to compensate also for the missing ankle torque.

### 2.5 The ANGELAA Prosthetic Leg

The prototype of the active knee prosthesis ANGELAA developed at the Sensory Motor Systems (SMS) Lab, ETH Zurich, has been used as test platform during this thesis. The device is a tethered powered prosthesis developed by Pfeifer et al. [72] to test different control strategies. Only the knee joint is actuated whereas for the foot and ankle a conventional prosthetic foot is used. The prosthesis has been specifically designed to allow for biomimetic modulation of the knee stiffness and knee moment-angle profiles during different gait activities. This was achieved using combination of a Series Visco-Elastic Actuation (SVEA) using special rubber bands and a Parallel Elastic Actuation (PEA) using two parallel springs. The main components of the powered prosthesis are shown in Fig. 2.8.a. A special socket, visible in Fig. 2.8.b, is used to allow tests with healthy subjects. An observer is used to accurately estimate force despite hysteresis in the rubber bands. The knee angle is measured by a 17bit absolute encoder (Netzer Precision Motion Sensors Ltd., Misgav, Israel), while redundant encoders (14bit, ams AG, Unterpremstaetten, Austria) are used on the opposite side for safety, such that a sensor fault can be detected. All sensor signals are sampled at 1 kHz and collected by a STM32 microcontroller. The signals are communicated at 1 kHz via a RS-485 connection to the xPC Target real-time computer (Speedgoat GmbH, Liebefeld, Switzerland), which runs the control algorithm at 1 kHz. To control the motor, a Maxon EPOS3 drive in current control mode is used. The motor drive communicates with the xPC Target by EtherCAT at 1 kHz.
Chapter 2. Learning from Nature

Figure 2.6: Subject walking in stance phase. (a) Comparison between the healthy hip torque profile (H, magenta) and the scaled prosthetic hip torque profile (P, blue). (b) Comparison between the healthy knee torque profile (magenta) and the scaled prosthetic knee torque profile (blue).

Figure 2.7: Subject walking in stance phase. Comparison between the GRFs of a healthy leg (H, magenta) and the scaled GRFs of a prosthetic leg (P, blue). The vertical GRFs are shown with a dotted line, while the anterior-posterior GRFs are shown with a continuous line.
Figure 2.8: ANGELAA active knee prosthesis. (a) CAD model of prosthetic leg showing main components. (b) Powered above knee prosthesis with special socket for healthy subjects.
Chapter 3

Design of Adaptive Impedance Controller

In this section, the major steps that have been taken for the implementation of a novel biomimetic adaptive impedance control are explained. In the first part of this chapter, an analysis on how different biomimetic impedance controllers for active prosthetics can be implemented is presented. The aim is to evaluate which is the best impedance model, between a NMS and a BK, to reproduce the human knee impedance. Then, the simulations and experiments conducted to test the two impedance models are presented. In the second part of this chapter, a novel adaptive impedance control that can be applied in parallel to the impedance controllers previously explained is proposed. Then, the simulations and experiments run to verify the performance of all the proposed controllers are described.

3.1 Impedance Control

In this section, four different biomimetic impedance controllers for active knee prosthetics are presented. To reproduce the structure of the human motion control, described in Sec. 2.1, a hierarchical impedance control architecture has been implemented. Two state-of-the-art HLCs, introduced in Ch. 1, will be tested for impedance control: the CLME control, and the Finite State Machine (FSM) control. Additionally, in this thesis two different impedance models are implemented for comparison purposes: the BK and the NMS impedance models, already introduced in Sec. 2.2.

3.1.1 Control Design and Preliminary Tests

Control Design

A CLME-based impedance control can be implemented as described in Fig. 3.1a and Fig. 3.1b, which represent, respectively, the control schemes using a BK and a NMS impedance model. The hierarchical subdivision of the control diagrams in HLC (green), MLC (blue) and LLC (violet) is visualized in both figures. The CLME estimates the user intention, as a set of impedance parameters, and communicates it to the MLC. In the MLC, an appropriate impedance model is used for converting the user intended state into an actual desired physical state for the device, i.e.
Table 3.1: Impedance parameters and transition thresholds for a BK state controller.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_{12}$</td>
<td>Position threshold between state 1 and 2</td>
<td>$10^\circ$</td>
</tr>
<tr>
<td>$\dot{\theta}_{12}$</td>
<td>Velocity threshold between state 1 and 2</td>
<td>5.73°/s</td>
</tr>
<tr>
<td>$\theta_{23}$</td>
<td>Position threshold between state 2 and 3</td>
<td>$20^\circ$</td>
</tr>
<tr>
<td>$\dot{\theta}_{23}$</td>
<td>Velocity threshold between state 2 and 3</td>
<td>5.73°/s</td>
</tr>
<tr>
<td>$\theta_{34}$</td>
<td>Position threshold between state 3 and 4</td>
<td>$50^\circ$</td>
</tr>
<tr>
<td>$\dot{\theta}_{34}$</td>
<td>Velocity threshold between state 3 and 4</td>
<td>0°/s</td>
</tr>
<tr>
<td>$\theta_{x1}$</td>
<td>Position threshold between state x and 1</td>
<td>$15^\circ$</td>
</tr>
<tr>
<td>$k$</td>
<td>Knee stiffness †</td>
<td>[3.84, 2.09, 1.40, 0.18] Nm/°</td>
</tr>
<tr>
<td>$b$</td>
<td>Knee damping †</td>
<td>[0.02, 0, 0, 0.02] Nms/°</td>
</tr>
<tr>
<td>$\theta_0$</td>
<td>Setpoint †</td>
<td>[8, 7, 70, 20]°</td>
</tr>
</tbody>
</table>

† Vector whose elements are the values of the parameter in each state (from 1 to 4).

Preliminary Simulation for NMS Model Stability Evaluation

Due to the presence of a time delay in the reflexive feedback loop and to the torque feedback of the GTO component, the NMS impedance model is potentially unstable. To have a preliminary evaluation of the stability of an impedance controller based on the NMS model, a forward simulation has been run using Matlab. In this way, it is theoretically possible to prevent that a test subject is injured during practical experiments. A human leg is modeled during stance phase as a double inverted pendulum, i.e. shank, thigh, with the ankle as pivot point on the ground (see Fig. 3.4). Two NMS impedance models control the joint torques at the ankle ($\tau_{ANMS}$) and knee joint ($\tau_{KNMS}$).

Physiological parameters for the NMS model obtained with SIPE were not yet available at the time of this thesis. The impedance gains and setpoints can be chosen freely because this simulation
3.1 Impedance Control

(a) CLME-based BK Impedance Control block diagram.

(b) CLME-based NMS Impedance Control block diagram. This scheme has not been implemented yet and its implementation is out of the scope of this thesis.

Figure 3.1: CLME-based impedance control block diagram with BK (a) and NMS (b) impedance models.
Chapter 3. Design of Adaptive Impedance Controller

Low Level Control

Mid Level Control

High Level Control

State Machine

State 2

Impedance Model

State 3

State 4

State

Figure 3.2: State Machine-based impedance control block diagram with BK (a) and NMS (b) impedance models.

(a) BK-based state impedance control.

(b) NMS-based state impedance control.

\( \tau_{\text{mdl}} \)
3.1. Impedance Control

Figure 3.3: Zoom on State Machine blocks from Fig. 3.1-3.2b. (a) State machine block diagram if a BK impedance model is used in the MLC. (b) State machine block diagram if a NMS impedance model is used in the MLC.
### Table 3.2: Impedance parameters and transition thresholds for a NMS_1 state controller.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_{12} )</td>
<td>Position threshold between state 1 and 2</td>
<td>10°</td>
</tr>
<tr>
<td>( \dot{\theta}_{12} )</td>
<td>Velocity threshold between state 1 and 2</td>
<td>5.73°/s</td>
</tr>
<tr>
<td>( \theta_{23} )</td>
<td>Position threshold between state 2 and 3</td>
<td>20°</td>
</tr>
<tr>
<td>( \dot{\theta}_{23} )</td>
<td>Velocity threshold between state 2 and 3</td>
<td>5.73°/s</td>
</tr>
<tr>
<td>( \theta_{34} )</td>
<td>Position threshold between state 3 and 4</td>
<td>50°</td>
</tr>
<tr>
<td>( \dot{\theta}_{34} )</td>
<td>Velocity threshold between state 3 and 4</td>
<td>0°/s</td>
</tr>
<tr>
<td>( \theta_{x1} )</td>
<td>Position threshold between state ( x ) and 1</td>
<td>15°</td>
</tr>
<tr>
<td>( k_i )</td>
<td>Knee intrinsic stiffness ↑</td>
<td>([2.09, 1.40, 1.40, 0.18]) Nm/°</td>
</tr>
<tr>
<td>( k_{ms} )</td>
<td>Knee reflexive stiffness ↑</td>
<td>([1.92, 1.05, 0.0]) Nm/°</td>
</tr>
<tr>
<td>( k_{gto} )</td>
<td>Knee GTO stiffness ↑</td>
<td>([0.1, 0.1, 0.1, 0]) Nm/°</td>
</tr>
<tr>
<td>( b_i )</td>
<td>Knee intrinsic damping ↑</td>
<td>([0.02, 0.02, 0.04, 0.02]) Nms/°</td>
</tr>
<tr>
<td>( b_{ms} )</td>
<td>Knee reflexive damping ↑</td>
<td>([0.01, 0.02, 0.0]) Nms/°</td>
</tr>
<tr>
<td>( \theta_{0} )</td>
<td>Setpoint ↑</td>
<td>([7, 7, 70, 20])°</td>
</tr>
</tbody>
</table>

† Vector whose elements are the values of the parameter in each state (from 1 to 4).

In this case, the transition between states 1 and 2 happens the second time that \( \theta < \theta_{12} \) while \( \dot{\theta} < \dot{\theta}_{12} \). Thus, it happens at the end of the stance flexion.

### Table 3.3: Impedance parameters and transition thresholds for a NMS_2 state controller.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_{12} )</td>
<td>Position threshold between state 1 and 2 ( \downarrow )</td>
<td>7°</td>
</tr>
<tr>
<td>( \theta_{12} )</td>
<td>Velocity threshold between state 1 and 2 ( \downarrow )</td>
<td>-0.60°/s</td>
</tr>
<tr>
<td>( \theta_{23} )</td>
<td>Position threshold between state 2 and 3</td>
<td>20°</td>
</tr>
<tr>
<td>( \dot{\theta}_{23} )</td>
<td>Velocity threshold between state 2 and 3</td>
<td>0°/s</td>
</tr>
<tr>
<td>( \theta_{34} )</td>
<td>Position threshold between state 3 and 4</td>
<td>50°</td>
</tr>
<tr>
<td>( \dot{\theta}_{34} )</td>
<td>Velocity threshold between state 3 and 4</td>
<td>0°/s</td>
</tr>
<tr>
<td>( \theta_{x1} )</td>
<td>Position threshold between state ( x ) and 1</td>
<td>15°</td>
</tr>
<tr>
<td>( k_i )</td>
<td>Knee intrinsic stiffness ↑</td>
<td>([1.43, 0.31, 1.40, 0.18]) Nm/°</td>
</tr>
<tr>
<td>( k_{ms} )</td>
<td>Knee reflexive stiffness ↑</td>
<td>([3.25, 0.21, 0.0]) Nm/°</td>
</tr>
<tr>
<td>( k_{gto} )</td>
<td>Knee GTO stiffness ↑</td>
<td>([0.1, 0.1, 0.1, 0]) Nm/°</td>
</tr>
<tr>
<td>( b_i )</td>
<td>Knee intrinsic damping ↑</td>
<td>([0.04, 0.02, 0.04, 0.04]) Nms/°</td>
</tr>
<tr>
<td>( b_{ms} )</td>
<td>Knee reflexive damping ↑</td>
<td>([0.04, 0.02, 0.0]) Nms/°</td>
</tr>
<tr>
<td>( \theta_{0} )</td>
<td>Setpoint ↑</td>
<td>([0.18, 6.70, 20])°</td>
</tr>
</tbody>
</table>

† Vector whose elements are the values of the parameter in each state (from 1 to 4).

‡ In this case, the transition between states 1 and 2 happens the second time that \( \theta < \theta_{12} \) while \( \dot{\theta} < \dot{\theta}_{12} \). Thus, it happens at the end of the stance flexion.
does not aim to model the physiological impedance of a human leg. In particular, the following restrictions are applied in order to run the simulation:

- **NMS Setpoint** - Shank and thigh trajectories, i.e. segment angles, from healthy gait data are used as reference feed-forward trajectories for the setpoint parameters.
- **NMS Gains** - The impedance gains are manually tuned. The tuning has been executed with a focus on position tracking of the desired shank/thigh trajectories.
- **Hip Forces and torque** - The hip forces \((F_{xH}, F_{yH})\) and torque \((\tau_H)\) of the simulated leg model are a replay, in time, of the forces/torques of the healthy gait data. In this way, the interaction with the upper body is guaranteed to be the same in the gait data and in the simulation. In Fig. 3.4, the hip forces are colored in light blue to distinguish them from the knee and ankle torques, in red, controlled using a NMS model.

Finally, to evaluate the stability and performance of the NMS model, the kinematics of shank and thigh of the simulated leg is compared with the gait data used for inverse dynamics. In particular, the maximum error and the Root Mean Square Error (RMSE) between the healthy and simulated angular trajectories of knee and ankle are evaluated. The RMSE is defined according to Eq. (3.1):

\[
RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (\theta_{Hj}^2 - \theta_j^2)},
\]

(3.1)

where \(\theta_j\) and \(\theta_{Hj}\) are, respectively, the simulated angle and the healthy angle, either of the knee or the ankle joint, and \(j\) indicates a sample over the stance phase of duration \(N\).

To have more information about the implementation of the simulation, please check the Matlab code C.1.4.1. More details about the EoMs for a double inverted pendulum can be found in section

![Figure 3.4: Simulation model of a healthy leg controlled at knee and ankle joint by a NMS impedance model and at the hip joint by commanded healthy torques and forces recorded using gait data.](image)
Table 3.4: Description of the test subjects.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Age</th>
<th>Weight</th>
<th>Height</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>25</td>
<td>85 Kg</td>
<td>1.79 m</td>
</tr>
<tr>
<td>SB</td>
<td>23</td>
<td>53 Kg</td>
<td>1.80 m</td>
</tr>
<tr>
<td>AP</td>
<td>29</td>
<td>59 Kg</td>
<td>1.80 m</td>
</tr>
</tbody>
</table>

B.2.1 of the Appendix. However, it is important to remind that the model in Fig. 3.4 is different from the double inverted pendulum presented in the Appendix. First, in the simulation model above, the interaction of the leg with the upper body is modeled using a set of healthy hip forces and torques, while in the model proposed in the appendix the upper body is modeled as a fixed HAT mass placed at the hip. Second, the ankle joint is here actuated by an ankle torque \( \tau_{ANMS} \), while in the appendix the ankle is passive, as in ANGELAA prosthesis. It is trivial to derive the EoMs for a double inverted pendulum, thus the computation will not be repeated.

### 3.1.2 Experimental Tests and Analysis

Preliminary tests to evaluate the performance of the BK and NMS impedance models were performed with three healthy subjects (RR, AP, SB) using the powered knee prosthesis ANGELAA (see Sec. 2.5). Details about the test subjects can be found in Tab. 3.4. The leg ANGELAA was controlled using a State Machine-based impedance control with the BK (impedance parameters in Tab. 3.1), the NMS\(_1\) (impedance parameters in Tab. 3.2), and the NMS\(_2\) models (impedance parameters in Tab. 3.2), which were introduced in Sec. 3.1.1. A FMS has been chosen instead of a CLME as HLC because the CLME control using a NMS model has not been implemented yet. To adjust the height of the subjects to the length of the prosthetic leg, an orthopaedic shoe with adjustable layers of metallic and rubber elements was used. The tests concentrated on treadmill walking at 3.0 Km/h for at least one minute. Additionally, each subject answered a usability questionnaire to compare the perception of the BK and NMS\(_1\) impedance model. The following aspects were covered:

- **Q1**: How natural is the perception of the NMS impedance model compared to the BK? 
  Range: 1 - Much worse, 5 - Much better.

- **Q2**: How stiff are the BK and the NMS impedance model? 
  Range: 1 - Not at all stiff, 5 - Very stiff.

- **Q3**: How difficult is to transit from stance to swing phase using a BK and a NMS impedance model? 
  Range: 1 - Too easy, 5 - Too difficult.

The analysis of the performance of the impedance models is based on the results of the usability tests, to evaluate the user perception, and on the following criteria:

- Qualitative analysis of the torque peaks and torque profile during stance phase. The average profile of the prosthetic torques is compared to an average healthy torque profile from Rienert et al. [79], which is scaled depending on the body weight of the test subject. As shown in Fig. 4.3, the torque peaks considered in the analysis are: extension peak torque, flexion peak torque, and stance to swing transition peak torque.

- Qualitative comparison between the average knee angular trajectory of the prosthetic leg and a healthy knee trajectory over one gait cycle.
The torque analysis is fundamental during stance phase and in the transitions between stance and swing phase. Indeed, these phases are the most critical in terms of user perception because the user’s stump is in contact with the environment through the leg. In addition, to reproduce a correct impedance, the qualitative analysis of the torque profiles/peaks is more fundamental than the quantitative comparison because, as mentioned in Sec. 2.4, the torque profiles have to be scaled depending on the user and on the properties of the device. To respect, qualitatively, the healthy torque profile, the magnitudes of the extension, flexion and transition peak torques have to be in the proportion 2 : 1 : 1, i.e. the magnitude of the extension peak torque has to be double the magnitude of the two other peaks.

On the opposite side, the position comparison is important during both stance and swing phase. On one hand, this is necessary to reproduce a natural movement, on the other hand, a correct motion guarantees enough foot clearance during the stride.

### 3.2 HMRAC - Human Model Reference Adaptive Controller

Adaptive control covers a set of techniques that provide a systematic approach for automatic adjustment of a controller in real time. One of the key points for designing a controller is the specification of the desired control loop performance. In many cases, the desired performance of the feedback control system can be specified through a reference model which represents the realization of the system with desired performance. According to Landau [55], there are two major implementation categories for adaptive controllers: a direct implementation (Fig. 3.5) and an indirect implementation (Fig. 3.6). In direct methods, the estimated parameters are directly used in the adaptive controller. In contrast, indirect methods are those in which the estimated parameters are used to calculate required controller parameters. In both cases, the design problem can be formulated as:

1. the error between the output of the plant and the output of the reference model is identically zero for identical initial conditions;
2. an initial error will vanish with certain dynamics.

When the plant parameters are assumed to be known under specific conditions, to achieve and to maintain the desired performance, a Model Reference Adaptive Control (MRAC) approach, shown in Fig. 3.5, can be considered. This scheme is based on the observation that the difference between the output of the plant and the output of a reference model (plant-model error) is a measure

![Figure 3.5: General direct adaptive control scheme (MRAC control).](attachment:image.png)
of the difference between the real and the desired performance. This information, together with other information related to the plant status, is used by the adaptation law to directly adjust the parameters of the controller in real time to asymptotically force the plant model error to zero.

Both, the choice of an appropriate plant model and the design of an efficient adaptation law are fundamental for the implementation of a good MRAC and thus they will be treated separately in the next sections. Finally, a general adaptive impedance control scheme is designed to test whether it is possible to improve the impedance modulation of the controllers introduced in Sec. 3.1.1.

In this thesis, the design of the MRAC is based on models (e.g. impedance models) and trajectories (e.g. knee trajectory) coming from human physiology. Therefore, as done by Engeberg et al. [21], the MRAC is renamed Human Model Reference Adaptive Control (HMRAC).

3.2.1 Control Design and Preliminary Tests

Modelling the Plant

The models that need to be used for the HMRAC design have to replicate accurately the dynamics of the desired plant to be controlled. Given the inherent differences in human leg dynamics during one gait cycle, it is necessary to use two different models for stance and swing phase.

A double inverted pendulum (thigh, shank) is used to model the leg in stance phase, while a double pendulum is used to model the leg in swing phase. The ankle joint is modeled as pivot point on the ground during stance phase and a HAT mass positioned at the hip is assumed to represent the upper body. Leg properties for the shank/thigh segments and the HAT are defined according to Winter [106]. Using the Newton-Euler method, the state space representations (Eq. (3.3)) of both models can be determined and a detailed description on their derivation is reported in Appendix B.2. The representation has the same structure in both cases and only the $A \in \mathbb{R}^{4 \times 4}$ and $B \in \mathbb{R}^{4}$ matrices are changed according to the model. The state vector $x \in \mathbb{R}^{4\times1}$ is defined by the angle and angular velocity of thigh and shank as

$$x = [\theta_t; \theta_s; \dot{\theta}_t; \dot{\theta}_s]. \tag{3.2}$$

The input to the system $u = \tau_{mdt} \in \mathbb{R}$ is the desired model knee torque of a specific impedance model, i.e. BK or NMS model.

$$\dot{x}(t) = Ax(t) + Bu(t), \quad x(0) = x_0$$

$$y(t) = Cx(t) \tag{3.3}$$

![Figure 3.6: General indirect adaptive control scheme (Adaptive Predictor Control).](image)
To obtain the desired closed loop dynamics of the system, the input of the state space is substituted with the characteristic equation of a desired impedance model. For simplicity, the BK impedance model is chosen to model the desired input torque  \( u \). Substituting the characteristic equation of the desired impedance model (e.g., Eq. (2.1) for the BK model) in (3.3), the desired closed loop dynamics (3.4) are:

\[
\dot{x}(t) = Ax(t) + B(wx(t) - k\theta_0), \quad x(0) = x_0 \\
y(t) = Cx(t)
\]  

(3.4)

with \( w = [k, -k, b, -b] \in \mathbb{R}^{1\times 4} \). Collecting common factors, the ideal closed loop dynamics using a BK impedance model can be rewritten as

\[
\dot{x}_m(t) = A_m x_m(t) + B_m (-k\theta_0), \quad x_m(0) = x_0 \\
y_m(t) = Cx_m(t)
\]  

(3.5)

where

\[
A_m = A + Bw, \\
B_m = B,
\]  

(3.6)

and the input to the state space, i.e. \( u_m(t) \), becomes now equal to \(-k\theta_0\). Unfortunately, in a real world application, the ideal model used for the design of the controller does not correspond to the real system that is controlled and innumerable uncertainties and perturbations can affect the system behaviour. A Parametric Uncertainty term (PU) can be used to model any kind of difference between the real plant and the model plant:

- Physical differences between different users and/or different real/prosthetic legs which are not considered either by the impedance model or by the leg dynamics (which are uniquely defined).
- Differences in the dynamics of the gait cycles.
- Perturbations due to the interaction with the environment.
- Missing ankle power.
- Different feet.

The term \( k_u(t) \in \mathbb{R}^{4\times 1} \) can be introduced as PU in the closed loop dynamics in order to represent all the possible uncertainties that make the dynamics of the real plant differ from the ideal closed loop dynamics (3.5) that we would like to reproduce. Let then the real system dynamics propagate according to the following differential equation:

\[
\dot{x}(t) = Ax(t) + B(u(t) + k_u^T(t)x(t)), \quad x(0) = x_0 \\
y(t) = Cx(t)
\]  

(3.7)

Assuming again the input knee torque to be equal to the torque of a specific impedance model, i.e. BK model as in (3.5), the equation (3.7) can be rewritten as Eq. (3.8) to find the real closed loop dynamics of the system:

\[
\dot{x}(t) = A_m x(t) + B_m (k_u^T(t)x(t) - k\theta_0) \\
= (A_m + B_m k_u^T(t))x(t) + B_m(-k\theta_0), \quad x(0) = x_0 \\
y(t) = Cx(t)
\]  

(3.8)
where
\[ u(t) = -k\theta_0, \]
\[ A_m = A + Bw, \]
\[ B_m = B, \]
(3.9)
\[ x(t) \in \mathbb{R}^{4\times 1} \] and \[ k_u(t) \in \mathbb{R}^{4\times 1} \] are respectively the state of the system (measured) and the vector of unknown parameters that should be suppressed. It is interesting to note that both the inputs to the ideal (3.5) and real closed loop dynamics (3.8) are defined by the stiffness \( k \) and setpoint \( \theta_0 \) of the desired BK impedance model.

**Adaptation Law**

To suppress \( k_u(t) \) from the real closed loop dynamics of the plant (3.8), an adaptive feedback law has to be defined. Given a uniformly bounded piecewise-continuous model reference \( y_m(t) \) from (3.5), the objective is to define the adaptive feedback law such that \( y(t) \) from the real plant (3.8) is able to track \( y_m(t) \), while all the signals remain bounded. The direct model reference adaptive controller is given by the previous closed-loop dynamics input plus an adaptive term:

\[ u(t) = -k\theta_0 - \hat{k}_u(t)x(t) \]
(3.10)
where \( \hat{k}_u(t) \in \mathbb{R}^{4\times 1} \) is an estimate of \( k_u(t) \). Substituting (3.10) in (3.8) yields the closed-loop system dynamics

\[ \dot{x}(t) = (A_m - B_m\hat{k}_u(t))x(t) + B_m(-k\theta_0), \quad x(0) = x_0 \]
\[ y(t) = Cx(t) \]
(3.11)
where \( \hat{k}_u(t) \triangleq \hat{k}_u(t) - k_u(t) \) denotes the parametric estimation error. Letting \( e(t)x_m(t) - x(t) \) be the tracking error signal, the tracking error dynamics can be written as

\[ \dot{e}(t) = A_m e(t) + B_m \hat{k}_u(t)x(t), \quad e(0) = 0. \]
(3.12)
The adaptation law for a MRAC can be designed using two possible methods: Lyapunov stability analysis or cost function-based design. In this thesis, the Lyapunov method has been used. The update law for the parametric estimate is given by

\[ \dot{\hat{k}}_u(t) = -\Gamma x(t)e^T(t)PFB_m, \quad \hat{k}_u(0) = k_{u0}, \]
(3.13)
where \( \Gamma \in \mathbb{R}^+ \) is an adaptation gain used to regulate how fast the adaptation takes place. \( F \geq 0 \in \mathbb{R}^{4\times 4} \) is forgetting matrix used for tuning purposes. \( P = P^T > 0 \in \mathbb{R}^{4\times 4} \) solves the algebraic Lyapunov equation

\[ A_m^T PF + PFA_m = -Q \]
for arbitrary \( Q = Q^T > 0 \). Consider the following Lyapunov function candidate:

\[ V(e(t), \hat{k}_u(t)) = e^T(t)PFe(t) + \frac{1}{\Gamma}e^T(t)\hat{k}_u(t). \]
(3.14)
Its time derivative along the system trajectories (3.12) - (3.13) is given by

\[ \dot{V}(t) = -e^T(t)Qe(t) + 2e^T(t)PFB_m\hat{k}_u(t)x(t) + \frac{2e^T(t)}{\Gamma}k_u(t)\hat{k}_u(t) \]
\[ = -e^T(t)Qe(t) + 2\hat{k}_u(T)(\frac{1}{\Gamma}k_u(t) + x(t)e^T(t)PFB_m) \]
\[ = -e^T(t)Qe(t) \leq 0. \]
(3.15)
Hence, the equilibrium of (3.12) - (3.13) is Lyapunov stable, i.e., the signals $e(t)$, $\dot{k}_m(t)$ are bounded. Since $x(t) = x_m(t) - e(t)$, and $x_m(t)$ is the state of a stable reference model, $x(t)$ is bounded. To show that the tracking error converges asymptotically to zero, we compute the second derivative of $V(e(t), k_m(t))$ as

$$\ddot{V}(t) = -2e^T(t)Q\dot{e}(t) \leq 0.$$  

It follows from (3.12) that $\dot{e}(t)$ is uniformly bounded, and hence $\ddot{V}(t)$ is bounded, implying that $\dddot{V}(t)$ is uniformly continuous. The application of Barbalat’s lemma yields

$$\lim_{t \to \infty} \dddot{V}(t) = 0,$$

which consequently proves that $e(t) \to 0$ as $t \to \infty$. Thus, $x(t)$ asymptotically converges to $x_m(t)$, which in turn implies that $y(t) = Cx(t)$ asymptotically converges to $y_m(t) = Cx_m(t)$ following the desired specifications. Notice that asymptotic convergence of parametric estimation errors to zero is not guaranteed. The parametric estimation errors are guaranteed only to stay bounded.

Using the Lyapunov design method just described, the convergence of the adaptive controller to a reference trajectory has been proven. According to Sec. 2.1, to show that the adaptation law is biomimetic, it is necessary to ensure that the control law can be tuned to use the minimum possible amount of energy (e.g. minimum effort/torque, [24]). As mentioned above, another design method based on cost functions can also be used for the design of a MRAC. To check that the adaptive control law meets all the biomimetic requirements [24], we can use the cost function method and compare its result to the outcome of the Lyapunov design. Consider a cost function $C(t)$ that is the sum of the two fundamental costs to be minimized by the adaptive control: an error in position $e(t)$ and a control effort term representing energy of the plant $E(t)$:

$$C(t) = e^T(t)Qe(t) + E(t).  \quad (3.16)$$

The energy term $E(t)$ can be approximated by the square of the control action $u(t)$ which represents the adaptive knee torque. Thus, (3.16) becomes:

$$C(t) = e^T(t)Qe(t) + \gamma u^2(t).  \quad (3.17)$$

We can minimize the $C(t)$ w.r.t. $u(t)$,

$$\frac{\partial C(t)}{\partial u(t)} = 2e^T(t)Qe(t) + 2\gamma u(t) = 0,$$  

and solving the minimization problem from Eq. (3.18) we find that

$$u(t) = \frac{1}{\gamma} \frac{\partial C(t)}{\partial u(t)} \propto \frac{1}{\gamma} e^T(t).  \quad (3.19)$$

Thus, to minimize both $e(t)$ and $E(t)$ at the same time, we need to use a control law $u(t)$ that is directly proportional to the kinematic error $e(t)$ and that is tunable according to a gain $\gamma^{-1}$. The gain $\gamma^{-1}$ defines a tradeoff between the minimization of the position error and the minimization of the energy that is applied to obtain a reduction in position error. When $\gamma$ is high, the weight of the energy term in the cost function (3.17) is high, thus the control effort will be small while the resultant position error will increase. Vice versa, when $\gamma$ is low, the weight of the energy term in the cost function (3.17) is low, thus the the control effort will be high and the resultant position error will decrease. The Lyapunov-based adaptive control, defined by (3.10) and (3.13), matches exactly the biomimetic requirements expressed mathematically using the cost function (3.16). Indeed, the the adaptation law is directly proportional to the error $e(t)$ and the gain $\Gamma$ has exactly the inverse role of the term $\gamma$ from (3.17). The higher is $\Gamma$, the higher will the adaptive control effort be and the smaller the position error, vice versa when $\Gamma$ is reduced.

Two major problems were faced during the implementation of this control strategy:
1. Due to the characteristics of human gait, the controller requires two separate control laws (based on two different models) for stance and swing phase.

2. To define the plant state, the control law requires information from both shank and thigh kinematics.

To solve the first issue, a switch between the two adaptation laws had to be implemented. Unfortunately, switching is always critical for control designs. To partially solve this issue, the two adaptive controllers are faded in/out at the beginning of each gait cycle (swing to stance transition) and in the stance to swing transition. Both fadings are executed using the method described in Fig. 3.7 for the transition between two generic phases, \( p_1 \) and \( p_2 \), independently if they represent stance or swing phase:

1. The total adaptive torque \( \tau_{adp} \) (dotted blue) is considered as the sum of the adaptive torque during \( p_1 \), i.e. \( \tau_1 \), and the torque during \( p_2 \), i.e. \( \tau_2 \), according to:

\[
\tau_{adp} = k_1\tau_1 + k_2\tau_2
\]

where \( k_1 \) and \( k_2 \) are two weighting factors used to fade in/out the torques. In the torque graph, the term \( k_1\tau_1 \) is represented by the continuous red profile and the term \( k_2\tau_2 \) is represented by the continuous black profile.

2. The adaptive control from \( p_1 \) is stopped \( 2^\circ \) before the transition threshold to phase two (\( \theta_{12} \)). Note that when the adaptive controller is stopped without resetting, it holds the last torque value, as shown by the red dotted line in the torque graph representing the profile of \( \tau_1 \).

3. The fading gain \( k_1 \) decreases linearly from 1 to 0 along the successive \( 4^\circ \) motion. Thus, the last stored adaptive torque value from phase one is faded out as a linear function of the knee angle.

4. The next phase’s adaptive torque \( \tau_2 \) is resetted and started at the beginning of the next phase. At the same time the fading gain \( k_2 \) goes from 0 to 1 instantaneously. For this reason, there is an overlapping of the two adaptive torques during the first \( 2^\circ \) of each phase, before the control action of the previous phase is completely faded out. This overlapping helps to smooth the transitions between the two controllers as shown by the resultant \( \tau_{adp} \) profile (dotted blue).

Due to the iterative resettings, this kind of adaptive control does not allow for learning between different gait cycles and, at the same time, never converges to a stiff position tracking control.

To solve the second issue, the thigh angle in the dynamic stance/swing leg models is assumed to be always constant at \( \pi/12 \) rad. In this case, the relation \( \theta = \theta_t - \theta_s = \pi/12 - \theta_s \) can be used to compute prosthetic knee angle \( \theta \) as a function of shank angle (and vice versa) and the dynamic model becomes fully defined using only the available sensory information about knee angle and torque.

User-Intended Desired Trajectory

The last missing component for the HMRAC implementation is the desired reference trajectory necessary for the adaptation law. The reference trajectory for the prosthetic leg has to be directly estimated from user intention. In this way, the adaptation mechanism can cooperate with the user such that the user does not feel driven by the prosthesis. The CLME method can be appropriately used to estimate the desired reference trajectory for the prosthetic leg. To account for
3.2. HMRAC - Human Model Reference Adaptive Controller

Figure 3.7: Explanation of the fading mechanism used to smooth the transitions between the adaptive control used in stance phase and the adaptive control used in swing phase. The graphs plot the transition between two generic phases $p_1$ and $p_2$. The first graph show the profiles of the fading gains of $p_1$ (red, $k_1$) and $p_2$ (black, $k_2$). The second graph shows the correspondent faded torque profiles (red/black continuous lines) and the resultant profile of the adaptive torque (dotted blue, $\tau_{adp}$). The red dotted line shows that the last value of the adaptive torque one $\tau_1$ is hold after the adaptive control one has been stopped.

Differences between different users, neglected by the standard contralateral mapping presented in the introduction Ch. 1, a new contralateral mapping has been designed [9]. The new mapping is trained from the sound leg of the specific prosthetic user while walking under controlled (ideal) laboratory conditions (Fig. 3.8). The movement of the sound leg is mapped to the movement of a desired healthy knee trajectory that is synchronized with the gait cycle of the user. This new training method allows to account both for the specific gait pattern of the user and to compensate for device-dependent delays that were not considered with the previous training method.

Figure 3.8: New contralateral mapping for online reference trajectory estimation
General Adaptive Control Scheme

The HMRAC controller designed above can be applied in parallel to both the CLME and State Machine based impedance controllers treated in Sec. 3.1.1, independently of the impedance model used (e.g. BK or NMS impedance models). Figure 3.9 describes the generalized control scheme that has been implemented on the active prosthesis ANGELAA to test the different impedance control strategies with adaptation. The control follows the hierarchical structure:

- **HLC**: At the HLC two possible controllers can be used to estimate the user intention. A CLME control can be used for direct estimation both of the impedance parameterers for the MLC impedance model \((params)\) and of the desired knee angular trajectory \((\theta_{ref})\) for the adaptive control. Alternatively, the HLC can be switched to a State Machine control. Unfortunately, a FSM does not allow to predict the desired knee angular trajectory, thus, in case the adaptive controller is used, it is necessary to use the CLME mapping for the estimation of the desired trajectory.

- **MLC**: In the MLC lies the core of the adaptive impedance control. First, the MLC level is made of the impedance model block, from which we can select the impedance model that more appropriately resembles the impedance of a human leg (e.g. BK or NMS model). Second, an adaptive control block can be used to add in parallel an additional torque component \(\tau_{\text{adp}}\) to the desired knee torque \(\tau_{\text{mdl}}\) determined by the impedance model. The additional adaptation torque component is used to adjust the impedance defined by the impedance model, as little as possible, to better track the desired knee trajectory \(\theta_{\text{ref}}\) estimated by the CLME.

- **LLC**: At the LLC an inner PI control loop is responsible for controlling the desired knee torque in the device. A vector \(w\) on the prosthetic leg represents all the uncertainties and perturbations that are influencing the dynamics of the device, and that the adaptive controller tries to suppress.

![General Adaptive Impedance Control Scheme](image-url)
3.2. HMRAC - Human Model Reference Adaptive Controller

Preliminary Forward Simulation for HMRAC Performance Evaluation

A forward simulation in Matlab has been implemented in order to have a preliminary evaluation of the performance of the adaptive controller. The prosthetic leg is modeled during stance phase using the same double inverted pendulum model (shank, thigh) that is used for the adaptive control design during stance, described in Appendix B.2. In the model, the ankle is represented as a pivot point on the ground (see Fig. B.2), a hat mass at the hip represents the human upper body, and the thigh angle is considered approximately constant $\pi/12$ rad during the entire stance. A set of random torque perturbations is applied at the knee joint, throughout the simulation, according to the torque model (3.20) (in Nm):

$$
\tau_{mdl} = -1020(0.44\sin(\pi/2t) - \theta) - 50(0.44\pi/2\cos(\pi/2t) - \dot{\theta})
- 1020(0.44\sin(3\pi t) - \theta) - 50(0.44\pi/2\cos(3\pi t) - \dot{\theta})
- 1020(0.44\sin(5\pi t) - \theta) - 50(0.44\pi/2\cos(5\pi t) - \dot{\theta}),
$$

(3.20)

where $\theta = \theta_t - \theta_s$ is the knee angle in radians, defined as the difference between thigh $\theta_t$ and shank $\theta_s$ angles. The adaptive control torque, when activated, is added in parallel to the random torque $\tau_{mdl}$. After $1.5$ sec from the beginning of the simulation, the adaptive control is turned on to follow a sinusoidal $\theta_{ref}$ angular trajectory described by 3.21:

$$
\theta_{ref} = 0.44 \text{ rad} \sin(\pi t) + 0.44 \text{ rad}.
$$

(3.21)

This simulation has the purpose on one side to check the stability of the HMRAC control designed above, and on the other side to check its performance in terms of position tracking, thus the position curves will be checked and compared to the reference trajectory (3.21) both in terms of smoothness and in terms of position accuracy using the the RMSE defined in Eq. (3.22):

$$
RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (\theta_{ref,j}^2 - \theta_j^2)},
$$

(3.22)

where $\theta_j$ and $\theta_{ref,j}$ are respectively the simulated knee angle and the reference angle, while $j$ indicates a sample over the stance phase of duration $N$. Furthermore, the torque profiles have also been analyzed to check the influence of the HMRAC to the impedance of the leg.

Preliminary Experiment for HMRAC Performance Evaluation

Before starting walking experiments with the HMRAC, the results of the Matlab simulation implemented above had to be verified. Thus, the behaviour of the adaptive control has been tested using a State Machine-based BK impedance control with the prosthesis ANGELAA. A healthy user wore the prosthesis using a special adapter, and an orthopaedic shoe with adjustable layers of metallic and rubber elements was used to adjust the height of the subjects to the length of the prosthetic leg. During the experiments, two static positions were tested: standing on both legs and standing only on the prosthetic leg. In these positions, the controller is tested in worst conditions because the body weight of the user is loading the leg and the state controller is in the fist state correspondent to the softest impedance of the gait cycle, i.e. impedance at the heel strike. To guarantee that the State Machine is kept in the first phase, a sinusoidal trajectory with amplitude $5.0^\circ$, offset $8.0^\circ$, and frequency $0.1$ Hz, has been used as reference trajectory for the adaptive control.

The position tracking performance of the adaptive control has been tested using the RMSE defined in Eq. (3.22) while the influence of the HMRAC to the impedance of the leg have been checked through qualitative analysis of the torque profiles.
3.2.2 Experimental Tests and Analysis

The walking experiments on the HMRAC were conducted with one experienced (RR) and two unexperienced healthy subjects (SB, AP) walking for at least 1.0 min on the treadmill at 3.0 Km/h. The subject RR tried also to walk at a higher speed, i.e. at 4.0 Km/h. Details about the test subjects are reported in Tab. 3.4. The prosthesis ANGELAA (see Sec. 2.5) was used as test platform. To adjust the height of the subjects to the length of the prosthetic leg, an orthopaedic shoe with adjustable layers of metallic and rubber elements was used. The general adaptive control scheme presented in Fig. 3.9 has been used to test all the possible impedance control combinations - introduced in Sec. 3.1.1 - with and without adaptation, according to the schematic in Fig. 3.10. In particular, the following controllers were tested:

**CLME-based Adaptive BK Impedance Control** In this impedance control, a CLME is used as HLC both for prediction of the impedance parameters and for the reference trajectory generation (see Sec. 3.2.1). The predictors for the CLME mappings are the kinematic measurements from two IMUs placed at the sound thigh and shank. In the MLC, a BK impedance model is used to model the impedance of a human leg and can be modified online if the HMRAC is activated.

**State Machine-based Adaptive BK Impedance Control** In this impedance control, a State Machine is used as HLC for prediction of the impedance parameters, while CLME is used for the reference trajectory generation. The predictors for the CLME mapping are the kinematic measurements from two IMUs placed at the sound thigh and shank. In the MLC, a BK impedance model is used to model the impedance of a human leg and can be modified online if the HMRAC is activated.

**State Machine-based Adaptive NMS Impedance Control** In this impedance control, a State Machine is used as HLC for prediction of the impedance parameters, while CLME is used for the reference trajectory generation. The predictors for the CLME mapping are the kinematic measurements from two IMUs placed at the sound thigh and shank. In the MLC, either a NMS1 or a NMS2 impedance model are used to model the impedance of a human leg and can be modified online if the HMRAC is activated.

Each subject answered a usability questionnaire to compare the perception of the impedance controllers tested with and without the HMRAC. The following aspects were covered:

![Figure 3.10: Experiments schematic. Each element of the table represents a specific test runned with RR, SB and AP. The BK model is tested using the parameters in Tab. 3.1. The NMS model is tested using two different sets of impedance parameters: NMS1 with parameters from Tab. 3.2, and NMS2 with parameters from Tab. 3.3.](image-url)
Q1: How much is the constraint on your movements exerted by the adaptive control?
Range: 1 - Not perceived, 5 - Too strong.

Q2: How natural is your perception/movement when the adaptive control is active?
Range: 1 - Not at all natural, 5 - Really natural.

Q3: How much difficult is to transit from stance to swing phase with and without the use of the adaptive control?
Range: 1 - Not at all, 5 - Too difficult.

The analysis of the performance of the impedance models is based on the results of the usability tests, to evaluate the user perception, and on the following criteria:

- Qualitative analysis of the torque peaks and torque profile during stance phase. The average profile of the prosthetic torques is compared to an average healthy torque profile from Riener et al. [79], which is scaled depending on the body weight of the test subject. The torque peaks considered in the analysis, shown in Fig. 4.3, are: extension peak torque, flexion peak torque, and stance to swing transition peak torque. Additionally, the maximum peak in adaptive torque over the gait cycle is recorded.

- Quantitative comparison between the average knee angular trajectory of the prosthetic leg and the reference trajectory from CLME using the maximum absolute error between the two trajectories and the RMSE defined as

\[
RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (\theta_{refj} - \theta_j^2)},
\]

where \( \theta_j \) and \( \theta_{refj} \) are respectively the prosthetic knee angle and the reference trajectory angle, and \( j \) is a sample over the stance phase of duration \( N \). Additionally, the angular trajectory of the prosthesis is also qualitatively compared with a healthy knee trajectory over one gait cycle.

Particular attention is dedicated to compare the differences between the impedance controllers, both in position and torque profiles, when the adaptive controller is used. The torque analysis is fundamental during stance phase and in the transitions between stance and swing phase, as presented in Sec. 3.1.2, due to the interaction with the environment. Ideally, the maximum adaptive torque has to be below 25.00 Nm in order to guarantee that the adaptive control does not modify the knee impedance too much. The position comparison is important during both stance and swing phase. On one hand, this is necessary to reproduce a natural movement, on the other, a correct motion guarantees enough foot clearance during the stride. Ideally, the RMSE when the adaptive control is used should tend below 5.0°, which is the human Smallest Perceivable Position Error in Lower Limbs (SPPELL).
Chapter 4

Results

4.1 Impedance Control

4.1.1 Control Design and Preliminary Tests

Preliminary Simulation for NMS Model Stability Evaluation

A simulation of a human leg during stance phase has been implemented in Matlab. The leg is modeled as a double inverted pendulum based on the model presented in Sec. 3.1.1. Two separate NMS impedance models (Eq. 2.2) control ankle and knee joint, while a set of human hip forces and torque is replayed at the hip joint.

Figure 4.1 shows the simulated position profile of the ankle and knee joint (in blue) compared to the human healthy trajectories used to define the setpoints for the impedance models (in red). The RMSE between the healthy and the simulated joint trajectories is equal to 2.71° (max 8.79°) in the knee joint and to 4.25° (max 9.34°) in the ankle joint.

Similarly, Fig. 4.2 shows the simulated torque profile of the ankle and knee joint (in blue) compared to the physiological human profile (in red). The simulated knee torque ranges from $-77.75 \text{ Nm}$ to $63.28 \text{ Nm}$, while the physiological knee torque ranges from $-32.99 \text{ Nm}$ to $23.45 \text{ Nm}$. The simulated ankle torque ranges from $-233.52 \text{ Nm}$ to $113.02 \text{ Nm}$, while the physiological knee torque ranges from $-107.29 \text{ Nm}$ to $7.40 \text{ Nm}$.

4.1.2 Experimental Tests and Analysis

An impedance controller using a BK and two NMS impedance models was tested using a State Machine as a HLC. The results of the tests with the experienced healthy subject (RR) are shown in Fig. 4.3 for the BK impedance model (red), the NMS$_1$ impedance model (blue), and the NMS$_2$ impedance model (black). Figure 4.3.a shows the averaged prosthetic knee angular trajectories over one gait cycle, while Fig. 4.3.b shows the averaged plot of the prosthetic knee torques. In the figures, the angular and torque profiles of the prosthesis are compared respectively with a healthy reference trajectory and a healthy torque profile from Riener et al. [79] (magenta, HLTY). Additionally, a comparison between the extension/flexion moments during stance phase is reported in Tab. 4.1.
Chapter 4. Results

Figure 4.1: Forward simulation of shank and knee angle during stance phase (blue). Human leg modeled as double inverted pendulum with knee and ankle torques controlled using the NMS impedance model. The angles are compared with healthy reference knee and ankle angular trajectories (red). (a) Ankle angle. Note that the ankle angle is here expressed as shank angle (segment angle instead of joint angle) because no foot is modeled. (b) Knee angle.

Figure 4.2: Forward simulation of ankle and knee torque during stance phase (blue). Human leg modeled as double inverted pendulum with knee and ankle torques controlled using the NMS impedance model. The torques are compared with healthy reference knee and ankle torques (red). (a) Ankle torque. (b) Knee torque.

The other two subjects tested (AP, SB) were able to walk only with the BK and the NMS1 model, thus their results are not compared here with the subject RR. For the interested reader, detailed information about their position and torque profiles can be found in Sec. 4.2.2. The results for the BK model are reported in Fig. 4.7 (red curve), Tab. 4.4 and Tab. 4.8. The results for the NMS1 are reported in Fig. 4.8 (red curve), Tab. 4.5 and Tab. 4.9.

The usability tests, runned with the three subjects (RR, SB and AP), gave the following results: the perception of the NMS1 impedance model over the BK impedance model is 3.67 (Scale: 1 -
Table 4.1: Peaks in extension and flexion knee torque during stance phase using the BK, NMS\textsubscript{1} and NMS\textsubscript{2} impedance models. Data from Fig. 4.3. Subject RR.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Extension Peak Torque</th>
<th>Flexion Peak Torque</th>
<th>Stance to Swing Transition Peak Torque</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>37.24 Nm</td>
<td>–17.79 Nm</td>
<td>18.28 Nm</td>
</tr>
<tr>
<td>BK</td>
<td>12.09 Nm</td>
<td>–17.93 Nm</td>
<td>20.56 Nm</td>
</tr>
<tr>
<td>NMS\textsubscript{1}</td>
<td>16.65 Nm</td>
<td>–15.53 Nm</td>
<td>17.27 Nm</td>
</tr>
<tr>
<td>NMS\textsubscript{2}</td>
<td>25.67 Nm</td>
<td>–7.14 Nm</td>
<td>3.55 Nm</td>
</tr>
</tbody>
</table>

Much worse, 5 - much better); the BK impedance model is stiffer than the NMS\textsubscript{1} impedance model (BK=4, NMS=3.33. Scale: 1 - not at all, 5 - too much); the NMS\textsubscript{1} impedance model allows for easier stance to swing transitions (BK=4, NMS=3. Scale: 1 - too easy, 5 - too difficult).

4.2 HMRAC - Human Model Reference Adaptive Control

4.2.1 Control Design and Preliminary Tests

Preliminary Forward Simulation for HMRAC Performance Evaluation

The results of a forward Matlab simulation of the prosthetic leg as a double inverted pendulum are presented in Fig. 4.4. In the simulation, the adaptive controller is activated after 1.3 sec as shown by the vertical red line.

The profile of the actual knee angle (blue) and the reference knee trajectory (red), used for the adaptive control, are shown in Fig. 4.4.a. The RMSE of the actual trajectory (blue) w.r.t. the reference trajectory (red) before and after the activation of the adaptive controller are respectively 16.34° (max 28.85°) and 0.31° (max 2.31°). After the activation of the adaptive controller, the actual knee trajectory of the prosthetic leg converges to the reference trajectory in 0.5 sec (settling time).

The knee torque profiles are shown in Fig. 4.4.b. The total knee torque acting on the knee joint is the sum of a perturbation torque (black), always active, and the adaptive torque. The perturbation knee torque (black) ranges from –583 Nm to 1884 Nm while the total torque, when the adaptive control is turned on, ranges between –6.04 Nm and 87.08 Nm.

Preliminary Experiment for HMRAC Performance Evaluation

The results of the preliminary experiment used to evaluate the performance of the adaptive controller are shown in Fig. 4.5. The adaptive control is activated after the red vertical line while the user is standing on both legs. A violet vertical line signals when the user starts to stand only on the prosthetic leg while the sound leg is lifted. Two vertical grey lines signal when the prosthesis is turned on, i.e. motor enable (left line), and off, i.e. motor disable (right line).

The actual knee angle profile of the prosthesis (blue) and the desired sinusoidal trajectory used for the adaptive control (red) are shown in Fig. 4.5.a. When the leg is activated and only a BK impedance model is active, the knee angle is constant in almost full extension with a constant
Table 4.2: Healthy peaks in extension and flexion knee torques during stance phase for each test subject (RR, AP, SB). Observe that the proportion between the peaks is always $\text{FlexionPeak : TransitionPeak : ExtensionPeak} = 1 : 1 : 2$.

value of 8.8° and a maximum position error of 5.8°. When the adaptive control is turned on, the knee angle converges to the reference trajectory in 1 sec (settling time), and the position error is reduced to a RMSE of 0.19° (max 0.40°).

The knee torque profiles of the prosthesis are shown in Fig. 4.5.b. The total knee torque acting on the knee joint is the sum of the impedance model torque (black), always active, and the adaptive torque. The impedance knee torque (black) ranges from $-19.13 \text{ Nm}$ to $19.80 \text{ Nm}$ while the total torque, when the adaptive control is turned on, ranges between $-18.15 \text{ Nm}$ and $-17.8 \text{ Nm}$. The maximum torque exerted by the adaptive control is $37.92 \text{ Nm}$.

4.2.2 Experimental Tests and Analysis

In this section, the results of the experiments runned accordingly to the schedule discussed in Sec. 3.2.2 (Fig. 3.10) are presented. In each of the cases tested - independently of the impedance model, high level controller, subject or test velocity - two separate plots are provided: one about the prosthetic knee position profiles with/without adaptation, and one about the prosthetic knee torque profiles, with/without adaptation. All the position and torque plots are plotted over one gait cycle and they are the average of multiple gait cycles.

In the position plots, the actual knee angular trajectory when the adaptive control is turned on ($\theta^*_k$, black) is compared with the trajectory when the adaptive control is off ($\theta_k$, red). Additionally, the figure plots also the averaged online reference trajectory used for the adaptive control ($\theta_{ref}$, dotted blue) and a healthy trajectory used for comparison ($\theta_{hlty}$, magenta).

In the torque plots, the knee torque when the adaptive control is turned on ($\tau^*_k$, black) is compared to the torque when the adaptive control is off ($\tau_k$, red). According to the terminology introduced in Fig. 3.9, the red torque profile is given by the desired impedance model torque ($\tau_{mdl}$), because no adaptation torque is applied in parallel to it. The continuous black profile is given instead by the sum of the BK impedance model torque ($\tau_{mdl}$, black dotted line) and the HMRAC torque ($\tau_{adp}$). A physiological torque profile from Riener et al. [79], scaled depending on the body weight of the test subject, is plotted in magenta ($\tau_{hlty}$). Details about the most important torque peaks in the healthy profiles of each test subjects are presented in Tab. 4.2. These peaks will be used for comparison with the torque data recorded during the tests.

CLME-based Apaptive BK Impedance Control

The results of the tests on the CLME adaptive impedance control based on the BK impedance model are presented in Fig. 4.6. Each column of the plots is associated to a different test subject.
walking at 3.0 Km/h: the first column to RR (Fig. 4.6.a1, Fig. 4.6.a2), the second column to AP (Fig. 4.6.b1, Fig. 4.6.b2), and the third to SB (Fig. 4.6.c1, Fig. 4.6.c2). The first row of the plots represents the knee angular trajectories with/without adaptation, while the second row of the plots represent the knee torque profiles with/without adaptation. All the plots are structured as described in the beginning of this section.

For each test subject, quantitative details from Fig. 4.6 are provided in Tab. 4.3 and in Tab. 4.7. Table 4.3 compares the position profiles throughout the gait cycle with and without the adaptive control. The data reported include maximum absolute position tracking error and RMSE w.r.t the reference trajectory. Table 4.7 compares the knee torque profiles during stance phase with and without the use the adaptive control. The data reported include: extension/flexion peak moments during stance phase, stance to swing transition moment, and maximum adaptive torque when the HMRAC is activated.

Additionally, the results of the same test with RR walking at 4.0 Km/h are shown in Fig. 4.10.a1 and Tab. 4.11 for the position profile, and in Fig. 4.10.a2 and Tab. 4.12 for the torque profile.

The usability tests, runned during the experiments, gave the following results: the constraint generated when the adaptive control is active is 2.67 (Scale: 1 - Not perceived, 5 - Too strong); the perception/movement when the adaptation is turned on is 3.17 (Scale: 1 - not at all natural, 5 - really natural); the stance to swing transition is as difficult when the adaptive control is on and when it is off (ON=2.83, OFF=3. Scale: 1 - not at all, 5 - too difficult). Two subjects commented that the oscillations from the CLME were slightly reduced when the adaptation was activated, and that the foot clearance was increased.

**State Machine-based Adaptive BK Impedance Control**

The results of the tests on the State Machine adaptive impedance control based on the BK impedance model are presented in Fig. 4.7. Each column of the plots is associated to a different test subject walking at 3.0 Km/h: the first column to RR (Fig. 4.7.a1, Fig. 4.7.a2), the second column to AP (Fig. 4.7.b1, Fig. 4.7.b2), and the third to SB (Fig. 4.7.c1, Fig. 4.7.c2). The first row of the plots represents the knee angular trajectories with/without adaptation, while the second row of the plots represent the knee torque profiles with/without adaptation. All the plots are structured as described in the beginning of this section.

For each test subject, quantitative details from Fig. 4.7 are provided in Tab. 4.4 and in Tab. 4.8. Table 4.4 compares the position profiles throughout the gait cycle with and without the adaptive control. The data reported include maximum absolute position tracking error and RMSE w.r.t the reference trajectory. Table 4.8 compares the knee torque profiles during stance phase with and without the use the adaptive control. The data reported include: extension/flexion peak moments during stance phase, stance to swing transition moment, and maximum adaptive torque when the HMRAC is activated.

Additionally, the results of the same test with RR walking at 4.0 Km/h are shown in Fig. 4.10.b1 and Tab. 4.11 for the position profile, and in Fig. 4.10.b2 and Tab. 4.12 for the torque profile.

The usability tests, runned during the experiments, gave the following results: the constraint generated when the adaptive control is active is 2 (Scale: 1 - Not perceived, 5 - Too strong); the perception/movement when the adaptation is turned on is 3.67 (Scale: 1 - not at all natural, 5 - really natural); the stance to swing transition is easier when the adaptive control is on (ON=1.33, OFF=4. Scale: 1 - not at all, 5 - too difficult). Two subjects commented that during the tests the end of the swing phase was too sharp when the adaptive control was active and one subject commented that there was an extremely positive difference in terms of perception between walking with and without the adaptive control.
State Machine-based Adaptive NMS Impedance Control

The results of the tests on the State Machine adaptive impedance control based on the NMS\textsubscript{1} impedance model are presented in Fig. 4.8. Each column of the plots is associated to a different test subject walking at 3.0 Km/h: the first column to RR (Fig. 4.8.a1, Fig. 4.8.a2), the second column to AP (Fig. 4.8.b1, Fig. 4.8.b2), and the third to SB (Fig. 4.8.c1, Fig. 4.8.c2). The first row of the plots represents the knee angular trajectories with/without adaptation, while the second row of the plots represent the knee torque profiles with/without adaptation. All the plots are structured as described in the beginning of this section.

For each test subject, quantitative details from Fig. 4.8 are provided in Tab. 4.5 and in Tab. 4.9. Table 4.5 compares the position profiles throughout the gait cycle with and without the adaptive control. The data reported include maximum absolute position tracking error and RMSE w.r.t the reference trajectory. Table 4.9 compares the knee torque profiles during stance phase with and without the use the adaptive control. The data reported include: extension/flexion peak moments during stance phase, stance to swing transition moment, and maximum adaptive torque when the HMRAC is activated.

Additionally, the results of the same test with RR walking at 4.0 Km/h are shown in Fig. 4.10.c1 and Tab. 4.11 for the position profile, and in Fig. 4.10.c2 and Tab. 4.12 for the torque profile.

The usability tests, run during the experiments with the NMS\textsubscript{1} model, gave the following results: the constraint generated when the adaptive control is active is 2 (Scale: 1 - Not perceived, 5 - Too strong); the perception/movement when the adaptation is turned on is 4.17 (Scale: 1 - not at all natural, 5 - really natural); the stance to swing transition is easier when the adaptive control is on but it is also not as difficult as with the BK model also when it is off (ON=1.33, OFF=2.67. Scale: 1 - not at all, 5 - too difficult). One subject commented that the swing phase was more natural when the adaptation was on. A different subject commented that the adaptive controller makes the transitions between the states smoother and that anyway the transitions are easier than with the BK impedance model in particular between stance and swing phase. The same subject commented that, in terms of movement and perception, the State Machine-based adaptive NMS control was the best one among the different strategies tested.

The results of the tests when the NMS\textsubscript{2} impedance model is used are presented in Fig. 4.9. Only one test subject (RR), out of the three tested, managed to walk at least one minute on the treadmill at a speed of 3.0 Km/h. The other two test subjects did not manage to walk properly with this set of impedance parameters and thus their results are omitted. The knee angular trajectory with/without adaptation for subject RR is shown in Fig. 4.9.a, while Fig. 4.9.b represents the knee torque profiles. Quantitative details from Fig. 4.9.a are provided in Tab. 4.6 related to the position profiles and in Tab. 4.10 related to the stance torque profiles. RR reports that this was the control combination that gave him the best perception during the interaction with the environment and that supported most the stance to swing transitions.
### 4.2. HMRAC - Human Model Reference Adaptive Control

<table>
<thead>
<tr>
<th>Subject</th>
<th>HMRAC</th>
<th>RMSE</th>
<th>Max Absolute Position Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>OFF</td>
<td>14.39°</td>
<td>39.47°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>8.91°</td>
<td>26.51°</td>
</tr>
<tr>
<td>AP</td>
<td>OFF</td>
<td>11.22°</td>
<td>27.32°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>5.07°</td>
<td>9.43°</td>
</tr>
<tr>
<td>SB</td>
<td>OFF</td>
<td>12.57°</td>
<td>32.18°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>10.23°</td>
<td>23.48°</td>
</tr>
<tr>
<td>mean</td>
<td>OFF</td>
<td>12.73°</td>
<td>32.99°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>8.07°</td>
<td>19.81°</td>
</tr>
</tbody>
</table>

Table 4.3: Position tracking errors when a CLME-based (adaptive) BK impedance control is used. The errors are defined between the actual prosthetic knee angle and the HMRAC reference trajectory during the entire gait cycle. Data from Fig. 4.6.

<table>
<thead>
<tr>
<th>Subject</th>
<th>HMRAC</th>
<th>RMSE</th>
<th>Max Absolute Position Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>OFF</td>
<td>9.50°</td>
<td>25.66°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>4.47°</td>
<td>11.35°</td>
</tr>
<tr>
<td>AP</td>
<td>OFF</td>
<td>23.79°</td>
<td>67.64°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>5.39°</td>
<td>13.26°</td>
</tr>
<tr>
<td>SB</td>
<td>OFF</td>
<td>18.45°</td>
<td>43.33°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>11.68°</td>
<td>25.54°</td>
</tr>
<tr>
<td>mean</td>
<td>OFF</td>
<td>17.25°</td>
<td>45.54°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>7.18°</td>
<td>16.72°</td>
</tr>
</tbody>
</table>

Table 4.4: Position tracking errors when a state (adaptive) BK impedance control is used. The errors are defined between the actual prosthetic knee angle and the HMRAC reference trajectory during the entire gait cycle. Data from Fig. 4.7.

<table>
<thead>
<tr>
<th>Subject</th>
<th>HMRAC</th>
<th>RMSE</th>
<th>Max Absolute Position Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>OFF</td>
<td>12.59°</td>
<td>35.51°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>7.31°</td>
<td>21.44°</td>
</tr>
<tr>
<td>AP</td>
<td>OFF</td>
<td>7.48°</td>
<td>15.05°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>4.94°</td>
<td>15.12°</td>
</tr>
<tr>
<td>SB</td>
<td>OFF</td>
<td>18.73°</td>
<td>39.76°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>4.44°</td>
<td>10.64°</td>
</tr>
<tr>
<td>mean</td>
<td>OFF</td>
<td>12.93°</td>
<td>30.11°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>6.77°</td>
<td>15.73°</td>
</tr>
</tbody>
</table>

Table 4.5: Position tracking errors when a state (adaptive) NMS₁ impedance control is used. The errors are defined between the actual prosthetic knee angle and the HMRAC reference trajectory during the entire gait cycle. Data from Fig. 4.8.
Table 4.6: Position tracking errors when a state (adaptive) NMS2 impedance control is used. The errors are defined between the actual prosthetic knee angle and the HMRAC reference trajectory during the entire gait cycle. Data from Fig. 4.9. The values reported are for a speed of 3.0 Km/h.

<table>
<thead>
<tr>
<th>Subject</th>
<th>HMRAC</th>
<th>Max Absolute Position Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>OFF</td>
<td>13.92°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>8.11°</td>
</tr>
</tbody>
</table>

Table 4.7: Peaks in extension and flexion knee torques during stance phase when a CLME-based (adaptive) BK impedance control is used. Data from Fig. 4.6.

<table>
<thead>
<tr>
<th>Subject</th>
<th>HMRAC</th>
<th>Extension Peak Torque</th>
<th>Flexion Peak Torque</th>
<th>Stance to Swing Transition Peak Torque</th>
<th>Max Absolute Adaptive Torque</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>OFF</td>
<td>10.70 Nm</td>
<td>−16.28 Nm</td>
<td>15.11 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>10.73 Nm</td>
<td>−13.78 Nm</td>
<td>7.26 Nm</td>
<td>12.05 Nm</td>
</tr>
<tr>
<td>AP</td>
<td>OFF</td>
<td>12.37 Nm</td>
<td>−14.78 Nm</td>
<td>4.96 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>7.38 Nm</td>
<td>−15.35 Nm</td>
<td>4.10 Nm</td>
<td>12.84 Nm</td>
</tr>
<tr>
<td>SB</td>
<td>OFF</td>
<td>10.58 Nm</td>
<td>−17.91 Nm</td>
<td>9.67 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>7.23 Nm</td>
<td>−20.82 Nm</td>
<td>6.35 Nm</td>
<td>23.80 Nm</td>
</tr>
</tbody>
</table>

Table 4.8: Peaks in extension and flexion knee torques during stance phase when a state (adaptive) BK impedance control is used. Data from Fig. 4.7.

<table>
<thead>
<tr>
<th>Subject</th>
<th>HMRAC</th>
<th>Extension Peak Torque</th>
<th>Flexion Peak Torque</th>
<th>Stance to Swing Transition Peak Torque</th>
<th>Max Absolute Adaptive Torque</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>OFF</td>
<td>13.72 Nm</td>
<td>−11.49 Nm</td>
<td>25.15 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>16.65 Nm</td>
<td>−15.53 Nm</td>
<td>17.25 Nm</td>
<td>17.67 Nm</td>
</tr>
<tr>
<td>AP</td>
<td>OFF</td>
<td>5.52 Nm</td>
<td>−12.75 Nm</td>
<td>16.38 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>5.26 Nm</td>
<td>−17.05 Nm</td>
<td>15.20 Nm</td>
<td>13.36 Nm</td>
</tr>
<tr>
<td>SB</td>
<td>OFF</td>
<td>8.69 Nm</td>
<td>−13.72 Nm</td>
<td>10.81 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>11.27 Nm</td>
<td>−23.84 Nm</td>
<td>16.05 Nm</td>
<td>29.04 Nm</td>
</tr>
</tbody>
</table>

Table 4.9: Peaks in extension and flexion knee torques during stance phase when a state (adaptive) NMS1 impedance control is used. Data from Fig. 4.8.
### Table 4.10: Peaks in extension and flexion knee torques during stance phase when a state (adaptive) NMS\textsubscript{2} impedance control is used. Data from Fig. 4.9. The values reported are for a speed of 3.0 Km/h.

<table>
<thead>
<tr>
<th>Subject</th>
<th>HMRAC</th>
<th>Extension Peak Torque</th>
<th>Flexion Peak Torque</th>
<th>Stance to Swing Transition Peak Torque</th>
<th>Max Absolute Adaptive Torque</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>OFF</td>
<td>19.62 Nm</td>
<td>−9.11 Nm</td>
<td>7.60 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>21.21 Nm</td>
<td>−13.80 Nm</td>
<td>8.85 Nm</td>
<td>16.01 Nm</td>
</tr>
</tbody>
</table>

### Table 4.11: Position tracking errors for the different control strategies. Tests runned at 4.0 Km/h with RR. The errors are defined between the actual prosthetic knee angle and the HMRAC reference trajectory during the entire gait cycle. Data from Fig. 4.10.

<table>
<thead>
<tr>
<th>Control</th>
<th>HMRAC</th>
<th>RMSE</th>
<th>Max Absolute Position Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLME BK</td>
<td>OFF</td>
<td>18.24°</td>
<td>43.82°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>15.99°</td>
<td>40.95°</td>
</tr>
<tr>
<td>State BK</td>
<td>OFF</td>
<td>9.45°</td>
<td>24.50°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>6.60°</td>
<td>27.26°</td>
</tr>
<tr>
<td>State NMS\textsubscript{1}</td>
<td>OFF</td>
<td>10.01°</td>
<td>28.40°</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>8.08°</td>
<td>20.39°</td>
</tr>
</tbody>
</table>

### Table 4.12: Peaks in extension and flexion knee torques during stance phase for the different control strategies. Tests runned at 4.0 Km/h with RR. Data from Fig. 4.10.

<table>
<thead>
<tr>
<th>Control</th>
<th>HMRAC</th>
<th>Extension Peak Torque</th>
<th>Flexion Peak Torque</th>
<th>Stance to Swing Transition Peak Torque</th>
<th>Max Absolute Adaptive Torque</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLME BK</td>
<td>OFF</td>
<td>2.70 Nm</td>
<td>−5.75 Nm</td>
<td>4.48 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>4.15 Nm</td>
<td>−13.05 Nm</td>
<td>10.54 Nm</td>
<td>12.88 Nm</td>
</tr>
<tr>
<td>State BK</td>
<td>OFF</td>
<td>11.83 Nm</td>
<td>−15.98 Nm</td>
<td>17.40 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>12.47 Nm</td>
<td>−14.46 Nm</td>
<td>17.90 Nm</td>
<td>13.67 Nm</td>
</tr>
<tr>
<td>State NMS\textsubscript{1}</td>
<td>OFF</td>
<td>15.06 Nm</td>
<td>−15.28 Nm</td>
<td>26.80 Nm</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ON</td>
<td>14.44 Nm</td>
<td>−15.94 Nm</td>
<td>19.95 Nm</td>
<td>15.11 Nm</td>
</tr>
</tbody>
</table>
Figure 4.3: Knee angle and torque comparison using a BK and two different NMS impedance models. Subject RR. (a) Knee angle using a BK impedance model (red), first NMS impedance model (blue), second NMS impedance model (black). (b) Knee torque using a BK impedance model (red), first NMS impedance model (blue), second NMS impedance model (black). Both knee torque and angle are compared to a set of physiological human data (magenta). The physiological torque profile shows the torque peaks used for qualitative analysis: I - Extension peak torque. II - Flexion peak torque. III - Stance to swing transition peak torque.
Figure 4.4: Knee angle and torque results from forward simulation of HMRAC used in stance phase to track a sinusoidal trajectory of offset and amplitude $15.0^\circ$ and frequency $0.5$ Hz. Prosthetic leg modeled as double inverted pendulum actuated at the knee joint. (a) Comparison between actual knee angle (blue) and reference angular trajectory (red) before and after the activation of the HMRAC. (b) Total knee torque profile (blue) and random torque perturbation (black) before and after the activation of the HMRAC. The total knee moment is equal to the sum of the random torque perturbation and the adaptive torque from HMRAC. The adaptive controller is turned on after the vertical red line, before it does not produce any torque.
Figure 4.5: Knee angle and torque results from experiments of the HMRAC used in stance phase to track a sinusoidal trajectory of offset 8.0°, amplitude 5.0° and frequency 0.1 Hz. (a) Comparison between actual knee angle (blue) and reference angular trajectory (red) before and after the activation of the HMRAC. (b) Total knee torque profile (blue) and impedance model torque (black) before and after the activation of the HMRAC. The total knee moment is equal to the sum of the impedance model torque and the adaptive torque from HMRAC. The adaptive controller is turned on after the vertical red line, before it does not produce any torque. The prosthetic leg is enabled between the two vertical grey lines. The user stands on the single prosthetic leg after the violet line.
Figure 4.6: Comparison of knee angle and torque profiles using a CLME-based BK Impedance control with and without adaptation. (a1), (b1), (c1) position profiles for the healthy subjects RR, AP and SB. (a2), (b2), (c2) torque profiles respectively for RR, AP and SB. In the knee trajectory plots, the actual knee trajectory with (black) and without adaptation (red) is compared to the reference trajectory used for the adaptive control (blue) and to a physiological healthy trajectory (magenta). In the knee torque plots, the total knee torque with (continuous black) and without adaptation (continuous red) is compared to a healthy torque profile scaled depending on body weight [79]. A dotted black line represent the impedance model torque while the adaptive control is turned on.
Figure 4.7: Comparison of knee angle and torque profiles using a State Machine-based BK Impedance control with and without adaptation. (a1), (b1), (c1) position profiles for the healthy subjects RR, AP and SB. (a2), (b2), (c2) torque profiles respectively for RR, AP and SB. In the knee trajectory plots, the actual knee trajectory with (black) and without adaptation (red) is compared to the reference trajectory used for the adaptive control (blue) and to a physiological healthy trajectory (magenta). In the knee torque plots, the total knee torque with (continuous black) and without adaptation (continuous red) is compared to a healthy torque profile scaled depending on body weight [79]. A dotted black line represents the impedance model. A dotted black line represents the impedance model.
Figure 4.8: Comparison of knee angle and torque profiles using a State Machine-based NMS1 Impedance control with and without adaptation. (a1), (b1), (c1) position profiles for the healthy subjects RR, AP and SB. (a2), (b2), (c2) torque profiles respectively for RR, AP and SB. In the knee trajectory plots, the actual knee trajectory with (black) and without adaptation (red) is compared to the reference trajectory used for the adaptive control (blue) and to a physiological healthy trajectory (magenta). In the knee torque plots, the total knee torque with (continuous black) and without adaptation (continuous red) is compared to a healthy torque profile scaled depending on body weight [79]. A dotted black line represent the impedance model torque while the adaptive control is turned on.
Figure 4.9: Comparison of knee angle and torque profiles using a State Machine-based NMS\textsubscript{2} Impedance control with and without adaptation. (a) position profiles for the healthy subject RR, walking at a speed of 3.0 Km/h. (b) correspondent RR’s torque profiles. In the knee trajectory plots, the actual knee trajectory with (black) and without adaptation (red) is compared to the reference trajectory used for the adaptive control (blue) and to a physiological healthy trajectory (magenta). In the knee torque plots, the total knee torque with (continuous black) and without adaptation (continuous red) is compared to a healthy torque profile scaled depending on body weight [79]. A dotted black line represent the impedance model torque while the adaptive control is turned on.
Figure 4.10: Comparison of knee angle and torque profiles using: (a) CLME-based Adaptive BK Impedance Control, (b) State Machine-based Adaptive BK Impedance Control, (c) State Machine-based Adaptive NMS_I Impedance Control. (a1), (b1), (c1) position profiles; (a2), (b2), (c2) torque profiles. Subject RR walking at 4.0 Km/h on the treadmill. In the knee trajectory plots, the actual knee trajectory with (black) and without adaptation (red) is compared to the reference trajectory used for the adaptive control (blue) and to a physiological healthy trajectory (magenta). In the knee torque plots, the total knee torque with (continuous black) and without adaptation (continuous red) is compared to a healthy torque profile scaled depending on body weight [79]. A dotted black line represent the impedance model torque while the adaptive control is turned on.
Chapter 5

Discussion

This thesis have been conducted in order to achieve two major objectives. The first goal is to realize in a prosthetic leg the physiological impedance modulation of a healthy leg during level ground walking. The second goal is to allow to an active knee exoprosthesis to adapt its impedance depending on the perturbations and uncertainties acting on the leg during the interaction with different users and different environments. To reach the first goal, two different impedance models - BK and NMS - have been tested using a state impedance control on the prosthetic leg ANGELAA. The NMS model results to be better than the BK if used with an appropriate set of impedance parameters. To reach the second goal, a HMRAC has been implemented. The adaptive controller allows to adapt online biomimetically the impedance of the prosthetic leg based either on a BK or on a NMS impedance model. The adaptation of the impedance allows to minimize, with the minimum energy consumption, the error in position of the prosthetic trajectory w.r.t. a desired reference trajectory. According to Ganesh el al. [24], this adaptation reflects the same adaptation principle used by the reflexes to change the impedance of the human body. In the following sections, the major results related to the objectives of the thesis are discussed.

5.1 Impedance Control

5.1.1 Control Design and Preliminary Tests

Preliminary Simulation for NMS Model Stability Evaluation

When this thesis started, no information about the sets of NMS impedance parameters for a human leg were available. To analyse the stability of the NMS impedance model/control before running experiments, a Matlab simulation has been implemented. As visible in Fig. 4.1, the trajectories of both the simulated knee and ankle joints are matching the correspondent healthy human trajectories and the average RMSE is smaller than 5.0°, which is the human Smallest Perceivable Position Error for Lower Limbs (SPPELL). No instability is evident from the simulation and the dynamics of the leg matches closely the dynamics of a human leg.

The torque profiles of the simulated leg (Fig. 4.2) are qualitatively close to the profile of the correspondent healthy torques, but they differ a lot in terms of magnitude. Anyway, the differences in torque profiles or GRFs are not taken into account, as there is no relation between the impedance values chosen for the simulated inverted double pendulum and the real values from healthy gait.
data. Indeed, the choice of the impedance gains and setpoints was completely free because this simulation has been purely a means to evaluate the stability of the NMS model and not yet its impedance profile.

5.1.2 Experimental Tests and Analysis

The BK and NMS impedance models have been experimentally tested using a FSM impedance controller. In particular, the NMS has been tested with two different sets of impedance parameters. The results on a healthy user (RR) walking at $3.0 \text{Km/h}$ are shown in Fig. 4.3 and Tab. 4.1.

As visible in Fig. 4.3.a, the BK and the NMS models have good position profiles if compared with a healthy trajectory, and only the BK model shows a slight delay of the swing phase. Analyzing the torque profiles in Fig. 4.3.b, the BK is worse than both the NMS impedance models. Indeed, if compared with a healthy torque profile, it has a rather small peak in extension torque (12.09 Nm), a normal peak in flexion torque (-17.93 Nm) and a too high peak in stance to swing transition (20.56 Nm). Due to the peak in the stance to swing transition, the user feels an uncomfortable virtual wall during the stance to swing transition. Thus, it is difficult to enter the swing phase, and the swing phase results to be often delayed.

The NMS\textsubscript{1} impedance model shows good flexion torque and stance to swing peaks - respectively - 15.53 Nm and 17.27 Nm - but has a too small extension moment. The NMS\textsubscript{2} shows instead, at least qualitatively, a better torque profile. In fact, the peak in extension torque is higher (25.67 Nm) than in the NMS\textsubscript{1} (16.65 Nm), and it is double the flexion and the stance to swing transition torques, which have almost the same magnitude of a healthy torque profile. Both the NMS\textsubscript{1} and NMS\textsubscript{2} allow for smoother transitions between the gait phases and in particular the stance to swing transition happens smoothly because the stance to swing peak torque is reduced.

It is important to remind that, for our purposes, it is desirable to reproduce the torque profile of a healthy leg, but this is not fundamental. On one hand, it is more important to reproduce the same qualitative shape of a healthy torque profile, i.e. same proportionality between the torque peaks, while the amplitude can vary a little. Indeed, the scaling relation in Sec. 2.4 shows that the prosthetic knee joint compared to a healthy knee has to provide a smaller torque (in amplitude) but with the same profile to compensate for the properties of the device. On the other hand, the prosthesis ANGELAA is not able to provide torques above 25.00-30.00 Nm in amplitude, thus it is physically impossible to reach the high torque peaks of a human knee, i.e. extension peaks.

The above analysis, at least for the comparison between BK and the NMS\textsubscript{1}, is confirmed by the opinions collected during the usability tests runned with RR, SB and AP. According to the healthy subjects, the NMS\textsubscript{1} impedance model gives a better and smoother perception than the BK, which is considered too stiff in particular in the stance to swing transition.

All in all, the NMS\textsubscript{2} model results to be the best impedance model for RR because it showed a good position profile, smooth transitions between the gait phases and qualitatively the best torque profile, with a correct proportionality within the torque peaks of the stance phase, i.e. 2 : 1 : 1. Unfortunately though, only RR was able to walk using the NMS\textsubscript{2} because this model has been optimally tuned for this specific subject. The NMS\textsubscript{1} can also be considered good because, although it has a slightly worse impedance profile than the NMS\textsubscript{2}, it can be used by different users. These results are very promising to show that the NMS impedance model is better than the BK model, and that an appropriate set of impedance parameters should be identified for each user in order to optimize the user’s performance, i.e. NMS\textsubscript{2} model for subject RR.
5.2 HMRAC - Human Model Reference Adaptive Controller

5.2.1 Control Design and Preliminary Tests

Preliminary Forward Simulation for HMRAC Performance Evaluation

The results of the forward simulation of the HMRAC to control the knee joint of a double inverted pendulum are quite promising. The adaptive controller is able to change the impedance of the knee such that the error in position, w.r.t. the reference trajectory, is reduced of 16.00° when the adaptation is turned on, and it is driven almost to 0° (Fig. 4.4.a). As can be seen in Fig. 4.4.b, the knee perturbation torque is active during the entire experiment with very high values that go up to 1884.00 Nm in absolute value. Although this torque is still acting at the knee when the HMRAC is turned on, the adaptive controller is able to generate an opposite torque that drive back the knee torque in the human range below 90.00 Nm.

In simulation, the HMRAC makes the knee angle converge to the desired trajectory in 0.5 sec (settling time). This convergency rate would be fast for other control applications but results to be quite slow for gait applications. Indeed, during level ground walking both the stance and the swing phase last less then 0.5 sec, so the adaptive controllers used for the two phases would never manage to converge exactly to the desired trajectory within one gait cycle. For our purposes, this is actually the desired behaviour of the HMRAC. In this way, we can ensure that with a proper tuning of the control gains the adaptive controller never converges too stiffly to the desired trajectory. If this happened, the controller would be too stiff and not an adaptive impedance control anymore, but rather a stiff position control.

Preliminary Experiment for HMRAC Performance Evaluation

The preliminary experiment runned with the prosthetic leg confirms the results on the adaptive controller that were suggested by the previous forward simulation. The adaptive controller is able to adapt the impedance of the prosthetic knee to track the sinusoidal trajectory both when the user is standing on both legs and when he is standing only on the prosthetic leg.

As visible in Fig. 4.5.a, the HMRAC is able to reduce the error in position tracking up to 0.19° with a maximum error of 0.40°. As desired, the controller results to adapt softly, with a ratio of convergency to the desired trajectory of about 5.3°/sec. As can be seen in Fig. 4.5.b, the knee impedance torque (model torque) and the total knee torque range both between -20.00 Nm and 20.00 Nm, which is within the range of human physiological torques. When the adaptive control is turned on, the impedance model torque has a steady state sinusoidal profile with amplitude 20.00 Nm and 0 Nm offset, while the total knee torque has almost a sinusoidal profile with amplitude around 6.0 Nm and a variable offset. The variable offset is due to the changing adaptive torque that compensates for the posture of the user during the test. The sinusoidal profile of the total knee torque, a part from the varying offset, is not respected only after the sound leg is lifted to compensate for the change in the dynamics of the human-prosthesis system.

The reference trajectory for this experiment has been chosen with a offset of 8.0° and an amplitude of 5.0° because this allows to test the HMRAC within the first state of the State Machine (0.0° < \( \theta_k < 15.00° \)). In this way, the performance of the adaptive controller has been verified in the worst test condition, when the knee impedance has the maximum stiffness, i.e. first state of the State Machine, correspondent to the heel strike impedance.
5.2.2 Experimental Tests and Analysis

CLME-based Adaptive BK Impedance Control

The first row of plots in Fig. 4.6 presents the position profiles of RR, AP and SB (left to right) when a CLME-based adaptive BK control is used. The position tracking RMSEs over the gait cycle are reported in Tab. 4.3 for each test subject. The average RMSE, among the subjects, is reduced from 12.73° (std 1.59°) when no adaptation is active to 8.07° (std 2.68°) when the HMRAC is used. This is a good result in terms of position tracking but it is still not optimal because the position error is above the human SPPELL (5.0°). As desirable, the maximum error in position during the entire gait cycle is reduced as well from 32.99° (std 6.12°) to 19.81° (std 9.11°). The position profiles using CLME without HMRAC result to be quite oscillatory among all the subjects and in two cases (RR, SB) the end of swing phase results to be delayed w.r.t both the physiological and the reference trajectory. When the adaptation is activated, the profiles are partially stabilized, towards the reference trajectory, and the swing phase delay is reduced. Unfortunately, during the tests has been noted that the performance of the HMRAC in position tracking and stabilization is highly dependent on the performance of the CLME both in terms of impedance prediction and reference trajectory generation. If either the impedance parameters are oscillatory or the reference trajectory is far from a physiological trajectory, the adaptive controller does not manage to stabilize the system and to converge to the desired trajectory. This is due to the fact that the adaptive controller, as desired by the biomimetic requirements, is exerting a soft/slow impedance modulation and not a stiff trajectory tracking.

The second row of plots in Fig. 4.6 presents the torque profiles of RR, AP, and SB (left to right). As discussed in Sec. 5.1.2, the BK model is worse than the NMS impedance models in terms of impedance modulation and torque profile. When the torque profiles without adaptation (red curve) are compared to the respective healthy torque profiles (magenta), all the three test subjects exhibit a peak in extension torque smaller than half the healthy peak, a too high peak in flexion torque, and a medium peak in the stance to swing transition. The values of the torque peaks for each test subject are also reported in Tab. 4.7, so they can be directly compared with the correspondent healthy torque peaks reported in Tab. 4.2. If the torque profiles are analyzed in qualitative terms, which are more important for our analysis (see Sec. 5.1.2), both the flexion and the stance to swing torque peaks are too high compared to the too small extension torque peak. Indeed, they should be in magnitude equal to half the magnitude of the extension torque, but they are instead bigger in all the tests. Nonetheless, the extension peak torque should be bigger in all the subjects. Additionally, due to the instability coming from the CLME prediction of the impedance parameters, the subjects RR and AP exhibit additional undesired torque peaks, so their torque profiles do not resemble the profile of a healthy torque. When the adaptive control is active, the torque profiles are all partly smoothed. In particular, the peaks in extension and flexion torques are not changed significantly, while the stance to swing transition torques are reduced in all the three subjects. This change in torque profile makes the leg move slightly more stably and eases the transition between stance and swing phase. The maximum change in torque due to the adaptive control is in average 20.02 Nm (std 8.10 Nm). Thus, as by requirements, the adaptive control does not change too much the impedance profile of each subject compared to the range of the respective healthy knee torque profiles.

According to the tests executed with RR walking at a higher speed, i.e. 4.0 km/h, the higher is the walking speed the worse is the gait pattern using the CLME-based BK impedance control. As visible from Fig. a1, at a high speed the subject experienced too high stance flexion and sharp stance-swing phase transitions. The motion of the leg results very unstable and difficult to be controlled, thus also the reference trajectory prediction is worsened. In these critical conditions, the position tracking performance of the adaptive controller is also reduced, and the RMSE (see Tab. 4.11) ranges between 18.24° without adaptation and 15.99° with adaptation, which is too high compared to the human SPPELL. Even when the adaptation is activated, the overall position
trajectory result to be far from physiological. The torque profiles, shown in Fig. 4.10.a2, are oscillatory and too small in magnitude either when the adaptation is on or off. The maximum adaptive torque is 12.88 Nm, which is as desired not too high for an adaptation in the impedance profile, but it is certainly too small to be able to correct the dynamics of the system if the behaviour of the HLC is totally not physiological.

The results from the usability tests confirms that the adaptation coming from the adaptive control is not too strong and the user does not feel constraint. The movement is overall more natural, while the stance to flexion transition happens quite easily with and without the adaptive control. Additionally the subjects reported that part of the oscillations in the controller were reduced using the adaptive controller and the foot clearance was increased.

State Machine-based Adaptive BK Impedance Control

The first row of plots in Fig. 4.7 presents the position profiles of RR, AP and SB (left to right) when a State Machine-based adaptive BK control is used. The position tracking RMSEs over the gait cycle are reported in Tab. 4.4 for each test subject. The average RMSE, among the subjects, is reduced from $17.25^\circ$ (std $7.22^\circ$) when no adaptation is active to $7.18^\circ$ (std $3.92^\circ$) when the HMRAC is used. In particular, the RMSE for two subjects out of the three tested was reduced to the range of $5.00^\circ$. This is a good result in terms of position tracking because the position error can be reduced, depending on the subject performance, to a range close to the human SPPELL. As desirable, the average maximum error in position during the entire gait cycle is reduced as well from $45.54^\circ$ (std $21.07^\circ$) to $16.72^\circ$ (std $7.70^\circ$). The position profiles, without the use of the adaptive control, show a step-kind shape at the beginning of stance phase and a slightly delayed swing phase. When the HMRAC is activated, the profiles result overall smoothed, and they converge more closely to the reference trajectory, i.e. the swing phase becomes more aligned with both the reference and the healthy trajectories.

The second row of plots in Fig. 4.7 presents the torque profiles of RR, AP, and SB (left to right). If the torque profiles without adaptation (red curve) are compared to the respective healthy torque profiles (magenta), all the three test subjects exhibit a peak in extension torque smaller than half the healthy peak, a medium/high peak in flexion torque, and a too high peak in the stance to swing transition. The values of the torque peaks for each test subject are also reported in Tab. 4.8, so they can be directly compared with the correspondent healthy torque peaks reported in Tab. 4.2. If the torque profiles are analyzed in qualitative terms, both the flexion and the stance to swing torque peaks are too high compared to the too small extension torque peak because they do not respect the healthy proportions, which should be respectively $1 : 1 : 2$. Nonetheless, the extension peak torque should be bigger in all the subjects. Unfortunately, this cannot be accounted by the adaptive control because in the beginning of the stance phase the position error is not high, thus the adaptive control does not modify the impedance of the leg. When the adaptive control is active, the torque profiles are partly smoothed. The peaks in extension and flexion torques are not changed significantly, while the stance to swing transition torques are reduced in all the three subjects. This change in the torque profile eases the transition between stance and swing phase, thus the delay in swing phase is reduced and the subjects can walk more naturally. The maximum change in the torque profile due to the adaptive torque is in average 16.44 Nm (std 8.38 Nm). Thus, as by requirements, the adaptive control does not change too much the impedance profile of each subject.

According to the tests executed with RR walking at a higher speed, i.e. 4.0 Km/h, when the speed is increased the performance of the adaptive control is slightly worsened but the gait pattern of the subject still results natural. As visible from Fig. 4.10.b1, the motion of the leg reflects pretty closely the trajectory profiles during the tests at lower velocity. Although the position tracking performance of the controller is reduced at this high pace, the RMSE (see Tab. 4.11) drops from
9.45° without adaptation to 6.60° with adaptation. This value of RMSE is still in an acceptable range, because it is close to the human SPPELL. Nevertheless, the velocity 4.0 Km/h is probably the highest possible speed in which the adaptive control is still adapting quickly enough to guarantee a good position tracking performance. Furthermore, the estimated reference trajectory from CLME (blue) is also worsened the higher is the speed. The torque profiles, shown in Fig. b2, have approximately the same profiles and peaks as the profiles at lower velocity. Only the stance to swing transition torque peak increases compared to the 3.0 Km/h case, but still this is not perceived by the user as uncomfortable (e.g., as virtual wall), due to the high pace and the proximity to the healthy torque profile. The maximum adaptive torque is 13.67 Nm, which is as desired not too high for an adaptation in the impedance profile.

The results from the usability tests confirm that the adaptation coming from the adaptive control is not too strong and the user does not feel constrained. The movement is overall more natural and the stance to swing transition happens much more easily for all the users. For what concerns the user perception, one subject commented that the improvement in comfort and perception given by the activation of the adaptive controller was immense.

State Machine-based Adaptive NMS Impedance Control

The first row of plots in Fig. 4.8 presents the position profiles of RR, AP and SB (left to right) when a State Machine-based adaptive NMS control is used. The position tracking RMSEs over the gait cycle are reported in Tab. 4.5 for each test subject. The average RMSE, among the subjects, is reduced from 12.93° (std 5.63°) when no adaptation is active to 6.77° (std 1.63°) when the HMRAC is used. In particular, the RMSE of one subject was reduced below 5.00°. This is a good result in terms of position tracking because it confirms once more that the position error can be reduced, with the HMRAC, to a range close to the human SPPELL. As desirable, the average maximum position error is reduced as well from 30.11° (std 13.21°) to 15.73° (std 5.43°). The position profiles for all subjects result overall smooth and with a natural trajectory both when with and without the use of the adaptive control. The only perceivable difference when the adaptive control is activated is that the swing phase becomes more aligned with the reference trajectory (blue).

The second row of plots in Fig. 4.8 presents the torque profiles of RR, AP, and SB (left to right). If the torque profiles without adaptation (red curve) are compared to the respective healthy torque profiles (magenta), the first two test subjects (e.g. RR and AP) exhibit a peak in extension torque smaller than half the healthy peak, a medium/high peak in flexion torque, and a too high peak in the stance to swing transition. The third subject exhibits instead a too small extension torque peak and good flexion and stance to swing transition peak. The values of the torque peaks for each test subject are also reported in Tab. 4.9, so they can be directly compared with the correspondent healthy torque peaks reported in Tab. 4.2. If the torque profiles are analyzed in qualitative terms, the flexion and the stance to swing torque peaks are too high compared to the too small extension torque peak because they do not respect the desired proportions, which should be respectively 1 : 1 : 2. Nonetheless, the extension peak torque should be bigger in all the subjects. To solve this issue, a different set of impedance parameters should be used. When the adaptive control is active, the peaks in extension torque is not changed significantly and the peak in flexion torque is increased. The stance to swing transition torque is reduced in the first two subjects and this case the stance to swing transition. In subject SB, even though the stance to swing extension peak increases, the subject is still able to swing easily thanks to the very high peak in flexion torque. The maximum change in the torque profile due to the adaptive torque is in average 20.02 Nm (std 8.10 Nm). Thus, also in this control combination, the adaptive control respects the requirements and does not modify too much the impedance profile of each subject.

As for the BK adaptive impedance control, when the speed is increased to 4.0 Km/h the performance
of the adaptive control is slightly worsened but the gait pattern of the subject RR still results natural. As visible from Fig. 4.10.c1, the motion of the leg respects a natural trajectory but the swing phase is now slightly anticipated compared to a physiological trajectory (magenta). Although the position tracking performance of the controller is reduced at this high pace, still the RMSE (see Tab. 4.11) drops from 10.01° without adaptation to 8.08° with adaptation. A RMSE of 8.08° is still sufficiently close to the SPPELL. Nevertheless, the velocity 4.0 Km/h is probably the highest possible speed in which the adaptive control can still improve the position tracking performance. Furthermore, the estimated reference trajectory from CLME (blue) is also worsened compared to the lower velocity. The torque profiles, shown in Fig. c2, have approximately the same profiles and peaks as the profiles at lower velocity. Though, it can be easily observed that the torque profiles are smoother than the torque profiles when a BK impedance model is used, in particular when the adaptive control is active. The maximum adaptive torque is 15.11 Nm, which is in the required range.

During the usability tests, all the subjects expressed that the State Machine-based NMS_1 adaptive control is, among the controllers tested, the best controller both in terms of user perception and in terms of natural movement. Additionally, the motion pattern and the perception were further improved when the adaptation was activated. Furthermore, the results confirm once more that the adaptation coming from the adaptive control is not too strong and the user does not feel constrained. One subject commented that, compared to the BK impedance control, the NMS control is smoother and more damped, in particular at the end of the swing phase. The adaptive controller results to be very useful because it helps to fasten the swing phase if it is too slow.

Although the analysis above states that the adaptive State Machine-based NMS_1 control has a good performance and that it is the best controller according to the usability tests, the analysis of his torque and position profiles did not show a substantial improvement if compared with the adaptive State Machine-based BK control. Indeed, the parameters used for the NMS_1 impedance model are, summing the stiffness and damping terms, in the same range of the BK impedance parameters. Therefore, there is no substantial change in impedance between the two models if not the one due the small GTO gain, the activation dynamics and the 40 ms delays in the reflexive loop.

The tests executed by RR with the NMS_2 are fundamental to show that, using a different set of impedance parameters for each user, the NMS impedance control performance can be further improved. The knee position profiles of RR, when a State Machine-based adaptive NMS_2 control is used, are shown in Fig. 4.9.a. The RMSE over the gait cycle, reported in Tab. 4.6, is reduced from 13.92° (max 43.86°) without adaptation, to 8.11° (max 23.95°) when the HMRAC is used. The RMSE is reduced to a value close to the range of the human perception threshold and thus, in terms of position tracking, the adaptive controller works as well as when the BK and NMS_1 models are used. When the adaptive control is used, the knee trajectory becomes more aligned with the reference trajectory and keeps a natural profile. As already seen in Sec. 5.1.2, the torque profiles in Fig. 4.9.b show that the NMS_2 model is much better in terms of impedance modulation than both the NMS_1 and the BK impedance models. Moreover, Fig. 4.9.b shows that the correct torque profile is preserved also when the adaptive control is used. Indeed, the profiles with/without adaptation respect exactly the desired proportions between the torque peaks as shown in Tab. 4.10. The maximum adaptive torque is in this case also in a good range with the value of 16.01 Nm.
To conclude, from the results presented above, the State Machine results to be better than the CLME as a HLC because it allows for a more stable and reliable impedance modulation. On the other hand, the CLME control is still fundamental and has some major advantages because it directly estimates the user intention and it is not based on discrete gait phases (e.g. states). Thus, if used to predict online the reference trajectory for the adaptive control, the CLME allows the adaptive controller to be user-cooperative even if a State Machine is used as a HLC.

Considering the adaptive control, the position tracking performance was sufficiently good, i.e. tending to the SPPELL, both with a State BK impedance control and with the two State NMS impedance control. In particular, the position tracking results to be always better during stance phase because the leg motion is slower, thus the HMRAC has enough time to act. The torque profiles and the resultant user perception were slightly more physiological, during stance phase, using a NMS\textsubscript{1} impedance model, and much more physiological (at least qualitatively) using the NMS\textsubscript{2} model. Unfortunately, only one subject managed to walk with the NMS\textsubscript{2} impedance gains, thus the NMS\textsubscript{1} results to be the best and more universal impedance model. Though, using an appropriate set of impedance parameters, a better NMS impedance model can be identified for each user, as demonstrated by the NMS\textsubscript{2} on RR. Furthermore, as shown by the maximum peaks in adaptive torque, the adaptive torque contribution to the impedance modulation is always smaller than 25.00 Nm as desired, thus the HMRAC never changes the impedance of the parallel impedance model too much.

One drawback related to the adaptive controller designed is that this kind of control tends to become easily unstable if high control gains are used. On one hand, this happens due to the differences between the segmented models used to design the controller and the real dynamics of the human/prosthetic leg. On the other hand, the prosthesis ANGELAA is actuated via SEA, thus it easily gets to instability using stiff controllers designed for tracking problems. To preserve stability, the control gains for the HMRAC have been set in a conservative way. This is good because it guarantees a soft and smooth impedance modulation comparable to the human modulation. Unfortunately, at the same time this makes the adaptation quite slow, so the controller is not able to react to perturbations with the same speed of the human reflexes. The experiments, runned at different speeds, confirm that the performance of the adaptive control starts to decrease for speeds higher than 4.0 \text{Km/h}.

A second drawback encountered during the tests is that when the adaptive control is used the prosthesis ANGELAA often overheats. This happens because the motor of the device has not been dimensioned properly, thus it overheats when the adaptive controller tries to call for torques higher than 25-30 Nm, which would actually be necessary to reproduce the range of torques of the human impedance.

A third drawback of the HMRAC is that its performance is highly influenced by the prediction of the impedance parameters and the reference trajectory from the HLC. If, as in the case of the CLME, the impedance prediction is far from the desired impedance or it is unstable, the control is at most able to stabilize a bit the system, but it is not able to change completely its impedance and drive it back to a physiological range.

All in all, among the controllers tested, the best controller results to be an adaptive State Machine-based NMS\textsubscript{1} impedance control because it gives a quite natural perception, it can be used with different subjects, and it is stable and reliable.

The tests on the performance of the adaptive control have some limitations because on one hand they have not been run with impaired subjects but with healthy subjects, on the other hand the hardware used, i.e. the ANGELAA exoprosthesis, is not powerful enough to generate torques in the range of the human physiological torques. The first problem implies that the mass and the kinematics of the prosthetic leg in the tests does not correspond to the kinematics and mass of a prosthetic leg wearied by an impaired user. In particular, the knee joint of the prosthesis is
not aligned with the knee joint of the sound leg, i.e. they have different height, and the total mass of the impaired leg, i.e. healthy leg with adapter and prosthesis, is superior to the mass of the leg of an impaired subject, i.e. stump with prosthesis. The second problem implies that the tests could not be performed for a long time because the motor easily overheated and the gait dynamics was also different because the torques are never as high as they could be with a more powerful motor. Moreover, the experimental parameters used in the tests for the NMS model were not yet available at the time of this thesis, so the author had to manually tune them starting from simulated values. Further research is necessary in this direction in order to identify real physiological parameters. Then, the experiments with the NMS impedance control should be repeated to verify if its impedance modulation can be improved.
Chapter 6

Conclusions

6.1 Conclusion

In this thesis, a biomimetic adaptive impedance controller for active lower limb prosthetics has been developed and tested with healthy subjects.

The first part of the thesis focuses on the identification of a good impedance model among the BK and the NMS models. The NMS model results from the test and the usability tests to be superior to the BK both in terms of physiological impedance modulation and in terms of user perception. In particular, the results of RR with the NMS2 model show that the model performance can be further improved if a specific set of impedance parameters is identified for each user. The torque profiles from the tests result to be qualitatively similar to the profile of physiological torques but they differ in magnitude. This is in line with the mathematical impedance scaling presented in the introduction, which shows that the torques in an active knee exoprosthesis are lower than the torques in a human leg because they have different mechanical properties. Additionally, the most important finding of the impedance scaling is that the knee joint in an active knee prosthesis is not able, in any case, to substitute the missing ankle power, but this has to be compensated from the hip joint. Unfortunately, at the time of this thesis, the parameters for the NMS model were not yet experimentally available, thus the author had to manually tune them based on simulated values. In the future, these values will come from user-specific perturbation experiments and the tests on the impedance models will have to be repeated again.

The second part of this thesis focuses on the design of an HMRAC used to modify the impedance of the prosthesis depending on the position error of the prosthetic leg w.r.t. a reference trajectory that is estimated online using CLME. The controller is able to reduce the RMSE in position below $8.0^\circ$ and in three test cases below the human SPPELL, i.e. $5.0^\circ$. The adaptation exerted by the HMRAC is soft and slow, i.e. the adaptive torque is always smaller than 25 Nm. Firstly, this avoids instability of the prosthesis and allows a smooth adaptation of the impedance. Secondly, also thanks to the fading mechanism developed to switch between gait phases, the adaptive control never converges to a stiff position control but it only adapts the leg impedance within a physiological range of torques. The performance of the adaptive control decreases for speeds higher than $4.0^\circ$, because above this range of speeds the adaptation is not fast enough to adapt the leg kinematics toward the reference trajectory. In terms of perception, all the users gave positive feedback both for the NMS impedance model and for the adaptive control when used with a FSM, because they allow for smooth transitions between the gait phases and they support the transition between stance and swing phase. Additionally, the adaptive control results to improve significantly the user perception and the state transitions also when a BK model is used. For what concerns the
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HLC, the most accurate and stable position tracking is obtained when a FMS is used. In terms of user-cooperativeness, the CLME control guarantees direct user intention estimation contrarily to the FSM. However, using a reference trajectory estimated via CLME, also the FSM results to be user-cooperative if the adaptive control is active. The CLME reference trajectory, trained for the first time on the impaired user, allows for a more accurate intention estimation because it accounts for the gait pattern of the specific user and for the control delays due to the hardware.

The tests on the performance of the adaptive control have some limitations because on one hand they have not been run with impaired subjects but with healthy subjects, on the other hand the hardware used, i.e. ANGELAA leg, was not powerful enough to generate torques in the range of the human physiological torques. The first problem implies that the mass and the kinematics of the prosthetic leg in the tests does not correspond to the kinematics and mass of a prosthetic leg wore by an impaired user, while the second issue led to short test times due to the overheating of the motor.

All in all, an adaptive state machine-based NMS impedance control results to be the best control strategy because it cooperates with the user, it modulates the impedance in a physiological way, it supports critical transitions between the gait phases (e.g. stance to swing) and it is perceived well during the entire gait cycle. This control strategy is used to replace one part of reflexes that is missing due to the missing limb. This adaptation does not affect the adaptation of the user, which is still adapting himself in parallel to the adaptive control, it rather cooperates with it.

6.2 Future work

This thesis presents a promising starting point for future research in adaptive impedance control for active prosthetics. In particular, the following aspects should be covered in more detail or improved:

- Once the NMS impedance parameters will be available from perturbation experiments with healthy subjects, the experimental tests with the NMS impedance model should be repeated.
- The HMRAC and the impedance models performance should be tested with more test subjects, in particular with amputees.
- The FSM performance should be further investigated. In the author’s opinion, this control strategy has a huge potential in terms of impedance modulation while preserving stability, reproducibility and reliability. The FSM could be improved increasing the number of states and choosing different state transition laws.
- To fully mimic the human reflexes, the HMRAC should be faster and slightly stiffer. Unfortunately though, to the author’s current knowledge, this is incompatible with the hardware of the prosthetic leg ANGELAA. Indeed, due to the presence of a SEA, the leg becomes easily unstable if a stiff tracking controller is used.
- The hardware of the prosthetic leg ANGELAA should be improved. First, the motor should be substituted with a more powerful motor. On one hand, this could guarantee the generation of torques in the range of 50 Nm, which is closer to the range of human physiological knee torques. On the other hand, the motor would not overheat anymore. Second, the SEA with rubber bands, should be either removed or substituted with springs. This would avoid hysteresis in the torque measurements due to the the rubber bands and would also remove (or decrease) the instability issues due to the SEA.
Appendix A

State of the Art Dissertation

This chapter gives an introduction to the state-of-the-art of active lower limb prosthetics around the world with a particular focus on control aspects.

A.1 Hardware and Control Strategies for Active Lower Limb Prosthetics

The first steps toward powered prosthetics were realized with the Belgrade transfemoral prosthesis in the late 1980s [78]. Compared to passive prostheses, energy consumption of an amputee was reduced and maximum walking speed was increased for the first time. The first active prosthesis was equipped with a DC motor to drive the knee joint using an external power supply. A couple of decades after only a few systems are able to inject energy and create torques actively in the knee and/or ankle joints. The majority of these systems originates from research institutions; only five devices are commercially available (Table A.1, modified from [33]). The first commercialized active foot was the Proprio Foot (Ossur, [68]). The powered foot-ankle prosthesis is equipped with accelerometers and angular sensors to detect the current state of the device and the most appropriate gait mode to be selected: level ground walking, stair climbing, sitting and relaxed. Using the information coming from these sensors, toe off, heel strike and last step information are recorded for pattern recognition of the actual gait phase, while foot inclination information is used for terrain detection and gait mode triggering. Based on the state of the device, the actuator drives the ankle into the correct position. The Proprio Foot can lift the toe during swing phase, ramp ascent and stair ascent to guarantee sufficient toe clearance. The toe is lowered during descent phases. In the Power Foot, an active ankle-foot prosthesis developed later by BiOM [10], a spring element with Achilles tendon like function is combined with a motor that mimics calf muscle. This new prosthetic ankle allows not only swing phase adaptation but also active push-off, which has been proven to be fundamental to achieve natural, i.e. almost unimpaired, and efficient gait, i.e. with low metabolic consumption [6, 29]. Powered ankle joints for walking and running were also developed at Springactive [85] and Westpoint Military Academy [40] based on a design from Arizona State University.

The first commercialized active knee prosthesis was Ossur’s Power Knee (Ossur, [68]). The device was presented to the market in 2006 and a new version was released in 2011. An actuator provides positive work during ascending/descending stairs and slopes, standing up and walking, and is able to dissipate energy during stairs descending and slopes. The motor lifts the heel for swing flexion and to accommodate the foot during touch down. As in the BiOM foot, a SEA element is storing
energy during stance phase flexion and releases it later to assist the motor. Martinez-Villalpando et al. showed that a similar device, i.e. active knee joint with antagonistic SEA element, can increase amputee’s walking speed up to 17% from 1.12 to 1.31 m/s compared to the C-Leg (Ottobock, [69]) and still reduces the metabolic cost by 6.8% [64]. At the Vanderbilt University, a combination of powered knee and ankle was developed [87]. The control of the prosthesis was further investigated and improved for several years at the Rehabilitation Institute of Chicago (RIC) to achieve good control performance during level ground walking, stair and slope climbing/descending, standing, sitting and, finally, running [83]. The leg will be further improved and commercialized by Freedom Innovations [49].

Table A.1: Overview on active lower limb prosthetics.

<table>
<thead>
<tr>
<th>Category</th>
<th>Group / Company</th>
<th>Name (if available)</th>
<th>Hardware</th>
<th>Control Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ankle</td>
<td>Springactive [85], USA</td>
<td>Odyssey</td>
<td>Actuator: Motor-parallel spring complex. Sensors: encoder, gyro.</td>
<td>Continuous control without states</td>
</tr>
<tr>
<td></td>
<td>Arizona State University and Springactive [41], USA</td>
<td>Sparky</td>
<td>Actuator: SEA, Maxon RE-40. Sensors: encoder, gyro sensor or optical switch at heel.</td>
<td>Position control or phase plane control [43]</td>
</tr>
<tr>
<td></td>
<td>Military Academy West Point [40], USA</td>
<td>Bionic Foot</td>
<td>Actuator: SEA, 2 x Maxon RE-40. Sensors: Motor encoder, gyro sensor.</td>
<td>Phase plane control</td>
</tr>
<tr>
<td></td>
<td>Springactive [85], USA (design) and TU Darmstadt, Germany (control)</td>
<td>Walk-Run Ankle</td>
<td>Actuator: Elastic motor-spring combination. Sensors: Motor encoder, gyro sensor, acceleration sensor.</td>
<td>Activity mode recognition for standing, walking, running and gait transitions.</td>
</tr>
<tr>
<td></td>
<td>Marquette University, USA [8, 86]</td>
<td>-</td>
<td>Actuator: 48V Maxon RE-40 graphite brushed motor with parallel linear torsional spring. Sensors: Optical encoder Maxon HEDL 5540 encoder</td>
<td>FSM both for torque and position control</td>
</tr>
<tr>
<td>Institution</td>
<td>Actuator Type</td>
<td>Actuator Details</td>
<td>Sensors/Control Methods</td>
<td></td>
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<tr>
<td>-------------------------------------------------</td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td>Sensors: Force sensing resistor at toe and heel, strain gauges at two springs,</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>two magnetic encoders at the ankle.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BiOM [6, 10, 20], Massachusetts Institute of</td>
<td>Power Foot</td>
<td>Actuator: SEA+UPS, Maxon EC-30, belt-transmission and ballscrew.</td>
<td>Neuromuscular reflex model.</td>
<td></td>
</tr>
<tr>
<td>Technology, USA</td>
<td></td>
<td>Sensors: Hall angular sensor at the ankle, strain gauges for spring force,</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>pyramid strain gauge for GRF, motor encoder.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peking University, China [110]</td>
<td>PANTOE</td>
<td>Actuator: Ankle - 83 W Faulhaber brushed DC, Toe - 45 W Faulhaber DC, ballscrew</td>
<td>Finite state control.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>transmission. Sensors: Encoder, touch and force sensors at heel and toe,</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>potentiometers at ankle and toe, potentiometer for ankle spring displacement.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kanazawa Institute of Technology [90]</td>
<td>-</td>
<td>Actuator: Unidirectional spring for controlling touch down plantarflexion.</td>
<td>Internal model control including learning</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Sensors: Ankle encoder.</td>
<td>from last step, ankle angle position control.</td>
<td></td>
</tr>
<tr>
<td>Ossur [68], Iceland</td>
<td>Proprio Foot</td>
<td>Actuator: Stepper motor. Sensors: Accelerometer, ankle encoder.</td>
<td>Artificial Intelligence with learning from</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>last step.</td>
<td></td>
</tr>
<tr>
<td>Institution</td>
<td>Actuator</td>
<td>Sensors</td>
<td>Control Method</td>
<td></td>
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<td>----------------------------------------------------------------------------</td>
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</tr>
<tr>
<td>Halmstad University, Sweden [91]</td>
<td>DC motor, only powered in swing phase, ball screw transmission. Sensors: Accelerometer at foot for slope estimation and gait phase detection.</td>
<td></td>
<td>FSM</td>
<td></td>
</tr>
<tr>
<td>Technical University Darmstadt, Lauflabor Locomotion Lab, Germany</td>
<td>SEA with variable stiffness, brushless DC motor. Sensors: Knee and ankle joint encoder, SEA force sensor, GRF sensor in the foot, gyro and accelerometer at the shank.</td>
<td></td>
<td>Speed related phase plane control similar to [43]</td>
<td></td>
</tr>
<tr>
<td>Knee University of California, USA [54,76]</td>
<td>Two linear hydraulic actuators with one pump, Maxon EC-30 for the pump, 40W. Sensors: Accelerometer and gyroscope at thigh, magnetic knee and ankle angle encoder, pressure sensor in hydraulic units, force transducer for sagittal plane moments and axial shank forces.</td>
<td></td>
<td>FSM</td>
<td></td>
</tr>
<tr>
<td>Islamic University of Technology and University of Dhaka, Bangladesh [50]</td>
<td>DC motor, 5 W, pulley. Sensors: EMG at thigh, encoder.</td>
<td></td>
<td>EMG based control</td>
<td></td>
</tr>
<tr>
<td>Massachusetts Institute of Technology, USA [64]</td>
<td>Actuator: Two antagonistic SEAs, Maxon RE-40 extension, Maxon RE-30 flexion, belt drive and ballscrew transmission. Sensors: Ankle encoder, motor encoder, spring compression measured by Hall sensor, insole force resistor for heel and toe contact.</td>
<td>FSM.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ossur [68], Iceland</td>
<td>Actuator: DC motor, harmonic drive gearing system. Sensors: Gyro, accelerometer, torque meter, ground contact sensor.</td>
<td>FSM.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMS Lab, ETH Zurich, Switzerland [72]</td>
<td>Actuator: Maxon EPOS3, Series (Visco-)Elastic Actuator (SVEA), PEA. Sensors: Optical quadrature motor encoder, contralateral hip and knee angle measured with goniometer/gyroscope or IMUs.</td>
<td>Complementary Limb Motion Estimation (CLME) or FSM.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clarkson University, USA [44, 45]</td>
<td>Actuator: Maxon RE-40, 150 W, ballscrew. Sensors: Load cell at knee for torque, knee potentiometer, pneumatic pressure sensors at heel and toe for ground contact, surface EMG from thigh muscles.</td>
<td>EMG based finite state linear impedance control.</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Ankle and Knee</strong> Vanderbilt University, USA. First version [88], second version [58]</td>
<td>Actuator: Motor+UPS at ankle, DD at knee, Maxon EC-30, 200W, ballscrew. Sensors: Series uniaxial load cell in each actuator unit, potentiometers at ankle and knee joint, strain based sagittal plane moment sensor between socket and knee, strain gauges at foot and heel for GRF.</td>
<td>Control: FSM and EMG based impedance control.</td>
<td></td>
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</tr>
</tbody>
</table>
During the last decades, notions of control have also been continuously expanding from the traditional closed loop-control concept to include different functionalities such as coordination, situation awareness, planning and diagnostics. In the world of lower limb prosthetics, it is generally possible to represent or schematize the various control strategies with a generalized structure. This generalized architecture is based on the well-known hierarchical control architecture [105] that is widely used in various highly complex systems, i.e. processing plants, manufacturing processes, aerospace vehicles [34], biomedical and human-robot interactive devices [19]. According to Tucker et al. [92], the hierarchical control architecture for prosthetic applications can be divided in a slightly different way compared to the one described in Sec. 2.1:

- **High Level Control (HLC).** This controller determines the user’s locomotive intent. The high level control interacts with the mid and low level controller via two possible strategies called Direct Volitional Control (DVC) and Activity Mode Recognition (AMR).

- **Medium Level Control (MLC).** The MLC receives the information from the HLC and converts from the estimated locomotive intent to a desired device state for the low level controller to track. There are multiple mid-level controls to accommodate the various activity modes and they can be roughly classified in phase-based controllers and non-phase-based controllers.

- **Low Level Control (LLC).** The purpose of the low level control is to calculate the error between the current and the desired state (i.e. output from the MLC) and act to minimize
A controller does not necessarily include all three layers. The HLC may be missing or may be included within the MLC.

A.1.1 High Level Control

The fundamental purpose of the HLC is to autonomously switch between different locomotion activities, ideally without impose any conscious inputs from the user.

Direct Volitional Control

The DVC allows the user to directly control the device’s state, i.e. joint position, velocity and torque. Direct volitional control is fundamental in conditions in which the locomotive task is irregular and non-periodic (e.g. queueing, waiting, walking on uneven terrains) and during non-weight bearing activities (e.g. leg voluntary repositioning). Myoelectric signals are the most widely used approach to volitional control of lower limb prostheses since they are already directly related to the control of voluntary movements. A first kind of DVC, used a couple of decades ago, directly modulates the actuator’s torque based on EMG signals [18]. A second kind of DVC, used nowadays, processes and maps the EMG signals to the set-point angle and gains of an impedance control law [36, 37, 44]. Goldfarb et al., at the Vanderbilt University, proposed the control of non-weight bearing activities based on pattern recognition of EMG sensory information [35]. Later, Hargrove et al. used the same device, at the Rehabilitation Institute of Chicago (RIC), to implement a new DVC based on pattern recognition using both mechanical and EMG sensory information during sitting [36]. Moreover, in the same group, a hybrid AMR and DVC implementing two neural control systems configured via LDA was investigated. Using this integrated control, different transfemoral amputees were able to walk as well as to perform weight transfers (e.g., sitting down and standing up) and seated non-weight bearing activities [84]. Hoover et al., at the Clarkson University, demonstrated the robustness and repeatibility of a EMG-based control system supplemented by a state-determined knee impedance control [45]. The implemented control provides an amputee subject with direct control of the knee torque during alternating stair ascent. The same group implemented also a third kind of DVC, which predicts the net joint torques based on a neuromusculoskeletal model and the EMG signals of appropriate joint flexor and extensor muscles [46]. Finally, at a different level, another kind of volitional control can be potentially learned by the user when he acclimates to the device. In this case, the user starts to be able to predict what the response of the device will be to a specific set of movements. However this kind of control is mostly related to MLC.

Activity Mode Recognition

The AMR is able to distinguish and switch between different gait modes thanks to their cyclic nature. To classify the gait modes, pattern recognition techniques and classifiers are commonly used. The inputs to the classifier, in general, include sensory informations coming from the user, the environment and the device. A different classifier can be chosen depending on its performance, i.e. errors in real-time applications, and the number of sensory inputs required, the number of gait modes to detect and classification latency. An appropriate choice of a specific classifier and the selection of the best sensory inputs are both fundamental for an accurate classification. The possible classifiers can be grouped in automated pattern recognition and heuristic rule-based classifiers.

In the automated pattern recognition approach, the classifier is firstly trained on a specific data set
A.1. Hardware and Control Strategies for Active Lower Limb Prosthetics

and during this process it automatically establishes specific classification decision boundaries. Once the boundaries are established for each class, the classifier is theoretically able to assign a class to each possible new data acquired. The most widely used classifiers include Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vectors Machine (SVM) and Artificial Neural Networks (ANN). Goldfarb et al. use QDA on the Vanderbilt leg [27, 35] while Hargrove et al. use LDA [38, 39, 107, 108, 113] and SVM [47] on the same device. Au et al. use ANN on the active ankle-foot prosthesis developed at MIT [5]. All the mentioned classifiers require an offline training based on data recorded from a group of healthy subjects. These training subjects are in general different from the user that will finally use the prosthesis and this can lead to major classification errors, regardless of the input sources to the classifier. According to Young et al., from the Hargrove’s group at RIC, classification accuracy is improved only if the training data set includes data recorded from the specific user [107]. An open research field is trying to establish how and if it is possible to identify universal inputs for the classifier such that their measures are almost constant all over the range of possible users. Then, it would be possible to apply the same classifier with a fixed offline training to each possible user.

In the heuristic rule-based classifier approach, the designer specifies a set of rules that indicate the transition from a gait mode to another. All the possible gait modes are known a priori. The transitions are based on Decision Trees (DT) or on Finite State Machines (FSM). DT are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from sample data’s features. DT have been recently successfully implemented by Zhang et al. for terrain recognition [111] and by Novak et al. for gait mode recognition [67], but both of them were tested without the use of a prosthetic leg. FSM is by far the most commonly used method between the heuristic rule-based classifiers. It is conceived as an abstract machine that can be in one of a finite number of states and switch from one state to another via transitions. A transition is initiated by a triggering condition, e.g. foot-floor contact, angular displacement/velocity of a specific joint, and elevation of the foot. The disadvantages of FSM are that usually the state classification goes together with a high latency up to one stride delay and the number of rules and thresholds that must be established increases exponentially with the numbers of gait modes. Often, ad hoc tuning for different users is necessary and it is important not to forget that the user is continuously adapting to the specific device thus the transition rules can be subjected to changes over time. FSM has been implemented by Popovic et al. on the Belgrade leg [77], by Varol et al. on the Vanderbilt leg [89], by Gorišč et al. on a new active knee-ankle prosthesis (project CYBERLEGs, [28]) and by Sun et al. on an active ankle prosthesis at Marquette University [86].

A.1.2 Mid Level Control

The MLC is responsible for converting the locomotive intent output coming from the HLC into a desired device state for the LLC to track. One of the most typical differentiation between MLC implementations is the division in phase-based controllers and non-phase-based controllers. The former depend directly on the gait phase while the latter are continuous. The MLC outputs the desired state of the device which consists in general of a combination of desired joint positions, velocities and torques.

One of the easiest ways of controlling a lower limb device is to use a position or velocity control, i.e. trajectory control, but not necessarily time dependent. This kind of control can be used if the mechanical impedance of the actuator is high w.r.t the load and surrounding environment or when the interaction forces with the environment are predictable/modelable. If the interaction forces cannot be characterized, as in typical human locomotion, the interaction with highly stiff and lowly damped objects can easily lead to instability [15, 104]. Popovic and Schwirtlich report the development of a finite state knee controller that utilizes a robust position tracking control algorithm for gait control of the Belgrade leg [77].
On the opposite, torque control is appropriate when the stiffness of the actuator is low w.r.t the environment, as is typical during locomotion. In prosthetics, impedance control is by far the most common control method utilized. A wide variety of virtual dynamics can be rendered using simple models based on spring-damping-inertia elements. A widely accepted hypothesis is that the CNS controls the limbs movements through impedance modulation [52, 93]. For this reason, more and more MLCs for prosthetic devices are moving in the direction of bioinspired impedance controllers that try to replicate the impedance of a healthy limb. Thus, an improved understanding on how humans control the impedance of the lower limbs is necessary to optimize the design and control of prosthetic devices [80].

Admittance control is the reciprocal concept of impedance control and it is usually adopted to modify the device’s dynamics. No literature about admittance control for lower limb prostheses has been found but its common application for lower limb orthoses [4]. Engeberg et al. used an admittance controller in a Human Model Reference Adaptive Control (HMRAC) to control an active prosthetic hand [21].

Phase-based Controllers

In time-based control, a set of actions is performed following a specific trajectory in time triggered by a clearly identifiable gait event. This technique is simple to realize but cannot be used in practice on lower limb prostheses due to the inherent irregularity and unpredictability of gait.

Invariant trajectories controller represent a more universal control strategy in which the desired system state is purely varying depending on the identified gait phase and it does not depend on gait speed and minor intra-gait-mode variations. It is also known as phase-plane control [43]. Universality is desirable but it is in practice unfeasible due to the natural differences in gait patterns, physical characteristics and intentions. The desired system state, i.e. position and velocity, directly depends on the gait phase and can be predicted using an invertible relationship between gait phase and invariant trajectories. This relationship can be found projecting a set of invariant trajectories on a specific set of axes. For instance, let us analyze the prosthetic ankle developed by Holgate et al. [43]. In this device, the controller can measure with a gyro sensor the shank angular velocity. By integration, shank angle in relation to the ground is determined. Using shank angle and velocity as axes, a (gait-)phase plot of the invariant trajectories can be determined (see Fig. 1.3) [40,41]. The resulting curves shown in Fig. 1.3, are for increasing stride length as the curves get longer. The coordinates, instead of being represented in Cartesian coordinates of angle and angular velocity, are represented by polar coordinates $\theta$ and $r$. The polar angle $\theta$ is related to gait percent by some function for each different stride length curve. Gregg et al. apply this control to the Vanderbilt leg at RIC and state that the relation found, between invariant trajectories and gait phase, can be considered independent of time, gait speed and ideally subject [30]. Indeed, the biggest advantage of this control is the possibility of automatic speed or step length adaptation during the gait cycle. Still, the question whether it is possible to apply this set of invariant trajectories to different users and with different physical impairments/patologies remains open [31]. In order to address this problem, Aghasadeghi et al. developed a two step controller estimation algorithm for an impedance control [3]. The first step of this algorithm is to use existing invariance in locomotion to produce joint trajectories corresponding to the locomotion of the amputee subject, i.e. locomotion trajectories that have been shown to be invariant across subjects and walking speeds. The second step uses the generated invariant joint trajectories in a model that utilizes the amputee’s physical characteristics, and is parameterized by controller parameters. The algorithm outputs the impedance controller parameters by solving a parameter estimation problem for ordinary differential equations (ODEs).

In a similar way, normalized-trajectory scales a prototypical joint trajectory extrapolated from a set of training gait data to match the physical characteristics and pace of a specific user. This
kind of control, defined “dynamic pace control” by Holgate et al., represents the normalized joint trajectory through a set of Fourier coefficients (Fast Fourier Transform, FFT) [42].

Echo control is a hybrid time-based and normalized-trajectory control. The joint trajectories of the sound limb are recorded and repeated in the impaired leg with a specific time delay and, in case, scaled or modified. This control has been designed some decades ago [32]. Soon, engineers realized that the Echo Control doesn’t work well in daily activities in which high unpredictability affects user’s movements. In fact, asymmetric activities or gait cycles with an odd number of steps represent an open challenge. Moreover, every undesired/compensatory movement that is recorded from the sound leg will also be replayed, which may affect the stability of the user. Anyway, this control is still in use nowadays by Wang et al. [101].

Finite State Controllers (FSCs) decompose the gait cycles as a periodic sequence of distinct phases, defined depending on the gait mode intended by the user. The phases are typically specified by constraints on limb kinematics (e.g. joint positions/velocities), foot contact, CoP position and others. A finite set of parametric control laws regulates the transitions between phases. The laws are based on a set of static parameters that are usually heuristically tuned. The tuning phase for transition laws for a specific user is indeed fundamental for the FSCs in order to optimize the user’s comfort and efficiency. A different FSC is required for each activity mode specified by the HLC. Sun et al. [86] describe the major requirements for a FSC that can be easily extended to almost all control strategies already presented:

- The gait has to be considered as repetitive, so the HLC can cycle indefinitely from last state back to the first one.

- The controller has to be able to identify gait phases and subphases during transitions and within them (i.e. useful when the controller is started from unknown conditions).

- The control needs to switch between different gait phases and different gait modes swiftly.

- Transitions between phases/subphases have to be safe and sure. Additional checking conditions have to be met when a new phase is triggered before switching from the current phase to the next one.

The FSC is currently the most frequently adopted controller and it has been implemented by many different groups and with a wide variety of devices, i.e. Varole, Fite, Goldfarb et al. apply it to the Vanderbilt leg at RIC [23, 57–59, 88, 98], Goršič et al. apply it to the CYBERLEGs ankle-knee prosthesis [28], Hoover et al. to the prosthetic knee at Clarkson University [45], Liu et al. to the Kanazawa’s ankle prosthesis [62] and Pfeifer et al. to the ANGELAA prosthesis. The major problem of this kind of control is related to complexity: in order to obtain an optimal performance from a FSC, ad hoc tuning is necessary. This tuning becomes more and more complex as the number of tunable parameters, number of phases, number of gait modes, number of joints to be actuated increases. Wang et al. recently designed a fuzzy control that automatically tunes the impedance parameters based on a set of heuristically inferred rules [100]. A second problem is related to sudden or unpredictable changes in user’s gait (e.g. sudden changes in gait mode, user fatigue, etc.). To overcome these problems, a couple of solutions have already been proposed. Herr et al. implemented a controller based on a neuromuscular model which has been proven to adapt to variations in terrain and gait speed using the Power Foot from MIT [20, 63]. Hoover et al. implemented an EMG-based controller that modulate a superimposed joint torque to the output of an underlying impedance control using the Clarkson University’s prosthetic knee [45].
Non-phase-based Controllers

Complementary Limb Motion Estimation (CLME) infers the intended motion of affected limbs from residual body motion [74, 96] and map this information to either a reference trajectory (if a position control is used, [96]), or to the coefficients and setpoints of an impedance model (if an impedance/admittance control is used, [75]). CLME is based on the strong inter-joint coordination that characterizes human motion [94, 102]. The CLME controller needs to be trained using data obtained from physiological gait data of healthy subjects. Using these data a mapping is trained by regression between residual limbs motion and impaired leg motion. It is a common mistake to confound CLME with echo control but they are indeed very different because CLME complements residual body motion without time delay, it is not related to the concept of gait phase (continuous control) and it doesn’t require a change in control between stance and swing phase. Similarly to echo control, the CLME requires as well instrumentation on the sound side of the body. This represent a big disadvantage in terms of daily-life usability (due to unpredictability) and it is only suitable for users that can still control certain body parts that are related to the specific kind of gait desired. Initially used for exoskeletons, the CLME was then proven to be an effective controller also for lower-limb prosthetic devices, e.g. for the knee active prosthesis developed at SMS Lab, ETH Zurich, during level ground walking and stair climbing [95]. This study demonstrated a reduction of compensatory movements using an active exoprosthesis commanded via CLME during level ground walking w.r.t. a commercial controlled-damping prosthesis (C-Leg, Ottobock [69]). It is still an open question whether it is possible to find an optimal unique mapping for different activities while reducing the number of sensory inputs.

A.1.3 Low Level Control

At the low level, torque, speed or position control are used to generate the desired motor trajectory. The LLC can be an inner level of the MLC, i.e. the inner loop of an impedance/admittance control, or can be intended as a specific separate controller (i.e. position control used for trajectory/path tracking). This controller is usually based on a feedforward and/or a feedback loop. The feedforward part is in general added to compensate for events/factors whose dynamics can be predicted and modeled with a certain degree of accuracy (e.g. friction compensation, gravity compensation, etc.). Very often, the LLC is realized as a PID controller, which can be static or dynamically changing depending on the system (e.g. adaptive PID). It is fundamental for the overall performance of the device that the LLC is properly chosen. Depending on the tuning of the controller the resultant perceived stiffness of the system is modified and depending on the bandwidth of the LLC, stability properties of the system are also affected [14]. Thus, particular care should be taken during the tuning and design of this controller, which is highly device-specific.

A.1.4 Sensors for Active Lower Limb Prosthetics

The control for active lower limb prostheses can account for a different number of inputs that can come from any number of sensors. The sensors may be worn by the user, implanted within the body or embedded in the prosthesis. They can be used to perceive user state, device state or environmental conditions. According to Grimmer et al. the control of a prosthetic device can be classified depending on the source of the input data, i.e. on the sensor type [33]. On one hand Computational Intrinsic Control (CIC) on the other hand Interactive Extrinsic Control (IEC) are possible. CIC has no direct connection to the user while IEC allows a direct or indirect communication between brain and device (see Fig. 1.1). This interaction can happen in the efferent command or in the afferent feedback signal. Both IEC and CIC have a direct correspondence with human sensory-motor system. IEC allows the triggering of different activities before a perceivable motion is executed. This represents an advantage w.r.t. CIC that can only act after
a motion already occurred. CIC is also found naturally in the reactive control mechanisms due to reflexes to the current motion. Indeed, reflex-like signals create basic motion patterns without brain interaction. Thus, it appears to be useful to have both approaches, CIC and IEC, combined in prosthetic control (e.g. in the case of EMG and mechanical fusion) to get advantages both on decentralized locomotion functions and on user-cooperative functions.

Electro-Mechanical Sensors for Computational Intrinsic Control

Body-worn electro-mechanical sensors measure forces or kinematic conditions of the system and/or of the environment. Electro-mechanical sensor-based control represents a CIC.

Sensors to measure forces and torques include Mechanomyography (MMG), load cells and pressure-sensitive insoles. Mechanomyography, also known as acustic/vibro-myogram, uses an accelerometer or a microphone to measure the vibrations/sound of the muscle fibers during contractions. The higher is the vibration due to contraction, the stronger the contraction. MMG have the potential advantage over EMG that the muscle force measurement is less sensitive to fatigue [70]. Recently, Beck et al. showed with a series of experiments that the MMG’s output is capable of tracking systematic changes in MMG amplitude and frequency with an increase in torque. However, these changes are statistically significant in only 26% of the cases [7]. Also other methods can be used to estimate a desired force production, e.g. via changes in muscle’s volume or muscle’s hardness, but as the MMG all these methods are highly sensitive to motion artifacts and thus cannot be yet used for intention estimation in a prosthetic device. Joint torques can instead be estimated via inverse dynamics if sufficient information about the system (e.g. mass, inertia, dimensions, etc.), external forces and joint positions are available.

Ground Reaction Forces (GRF) can be sensed using insoles worn under the foot [1] or by measuring the load in the prosthetic shank via load-cell [53]. GRFs information can be used for control purposes as joint torque estimation or switching condition (e.g. foot switches). Other foot switches can also be used to provide binary information about the ground contact using pressure sensors and force-sensitive resistors (FSRs). Novak et al. present algorithms for detection of gait initiation and termination using wearable IMUs and pressure-sensitive insoles [67]. Body joint angles, joint angular velocities, GRFs and COP of each foot are obtained from these sensors and input into supervised machine learning algorithms. The initiation detection method recognizes two events: gait onset (an anticipatory movement preceding foot lifting) and toe-off. The termination detection algorithm segments gait into steps and determines whether this measurement belongs to the final step. So far, this method has been successfully tested on unimpaired subjects so it is unclear how well this can be translated to pathological gait.

Embedded mechanical sensing represents an appealing alternative to estimate the device’s state because the sensors are fully embedded in the device and do not need to be worn separately. This is for instance the main advantage of the Power Knee from Ossur [68] compared to every other existing device. Varol et al. implemented a switching algorithm that infers the user intent to stand, sit and walk, by recognizing patterns in the prosthesis sensor data in real time, without need of extra instrumentation of the rest of the body [98]. Appropriate sensor information includes joint angles and angular velocities (i.e. knee and/or ankle joints), in addition to measured interaction forces and/or torques between the user and prosthesis, and between the prosthesis and environment.

Wearable sensors to measure joint position and/or segment orientations include accelerometers, goniometers, gyroscopes, magnetometers and inertial measurement units (IMUs) [82]. A particular attention can be dedicated to the last three that are currently used for CLME-based control of the active prosthetic leg at the SMS Lab (ETH, Zurich). Environmental sensing can be used to add valuable information to the controller regarding terrain condition and context that can be used to trigger a mode transition. The state of the environment can be directly detected or indirectly
Appendix A. State of the Art Dissertation

derived based on the state of the user/device. Zhang et al. developed a terrain recognition system made of a laser distance sensor and IMUs to recognize the height and slope of the ground [111]. Scandaroli et al. used instead gyroscopes and infrared sensors for the same application [81]. It is also possible to infer properties of the terrain directly from the state of the device, e.g. using an accelerometer mounted on the foot or IMUs that detect the orientation of the segment on which they are attached [22,61].

Electromyography for Interactive Extrinsic Control

EMG is the most intuitive way to physically read motion intention signals coming from the Central Nervous System (CNS), which is responsible for motion control. In general, when the user voluntarily generates muscle contractions, control information is extracted via EMG (e.g. amplitude, rate of change in amplitude), and the appropriate DoF is actuated. The EMG can be surface based, which is the less invasive and the mostly used method, or based on intramuscular recording of modulated motoneurons’ activity via intramuscular fine-wires, i.e. after targeted reinnervation, as in Li et al. [60]. Targeted Muscle Reinnervation (TMR) is a surgical operation in which residual nerves from the amputated limb are transferred to alternative muscles that are no longer biomechanically functional. The reinnervated muscles serve as a biological amplifier for neural commands sent through the nerves. Using the amplified signals detected via surface EMG a phase dependent locomotion mode classifier can be implemented [48]. Surface EMG has been used by Jin et al. for the classification of six activity modes, used to identify different kinds of terrains [51]. A similar study was conducted by Huang et al. who managed to increase the accuracy in the detection of seven distinct gait modes through the use of a phase-dependent LDA classifier [48]. Miller et al. [65] developed a myoelectric walking mode classifier for transtibial amputees over seven distinct gait modes. Using LDA and SVM the detection of all seven walking modes had an accuracy of 97.9% for a test over a group of five amputees. Misclassifications between different modes occur most frequently between different walking speeds due to the similar nature of the gait pattern. Stair ascent/descent has in general the highest classification accuracy due to its distinct pattern compared to the other gait modes. Zhang et al. investigated the usefulness of different data sources commonly suggested for user intent recognition, i.e. eight surface EMG signals from the residual thigh muscles of amputees, GRFs from a prosthetic pylon, and kinematic measurements from the residual thigh and prosthetic knee. The experiments showed that EMG signals and GRFs were more informative than the kinematics of the prosthesis.

Electromyographic and Mechanical Sensor Fusion

Currently the research is evolving to increase the robustness and reliability of pattern recognition techniques based on EMG and promising improvements seem to come from the synchronous use of EMG and electromechanical sensors. Huang et al. was the first group to try this approach in 2011 and they showed that neuromuscular-mechanical fusion outperforms methods that use only EMG or mechanical information [47]. During steady state walking, the control based on neuromuscular-mechanical fusion produced 99% or higher accuracy in locomotion-mode recognition in stance phase, and 95% accuracy in swing phase. In particular, this SVM-based control correctly recognized all transitions with a sufficient predication time. The same work was then continued over the years by Young et al. [107]. The same group improved further this method introducing a Dynamic Bayesian Network (DBN) classifier instead of a SVM or LDA classifier [109]. The DBN for transitional and steady-state stair steps had a high recognition rate (>99%), while ramp steps were significantly more difficult to classify.
Appendix B

Dynamic Segmented Models of Human Body

B.1 Three-Segmented Model of Amputee Gait

As introduced in Sec. 2.4, to find a scaling between the impedance of the prosthetic knee joint and a healthy knee joint the inverse dynamics of their respective models have to be derived. In this section, the inverse dynamics of a model of amputee gait is implemented following the assumptions described in Sec. 2.4. As shown in Fig. B.1, the upper body, i.e. the HAT, the residual leg and the transfemoral prosthesis of an amputee can be modeled by three segments. In contrast to the model of unimpaired gait, here prosthetic shank and foot are combined as the prosthesis segment. The segments are connected by two hinge joints representing the knee and the hip joint. Mass, Inertia, CoM and length of each segment are defined using anthropometric data [106] and characteristics of the prosthetic leg ANGELAA. The model is restricted to two dimensions, i.e. to the sagittal plane. The segment angles are defined w.r.t the vertical axis, and positive angles are counted counter clockwise. The Newton-Euler method is used to derive the EoMs for the stance phase during a nominal gait cycle. According to the requirements in Sec. 2.4, assume:

- Hip trajectory \((x_H, y_H)\), knee trajectory \((x_K, y_K)\), ankle trajectory \((x_A, y_A)\) and (consequently) segment angles, i.e. \((\theta_s, \theta_t, \theta_{hat})\), are a set of generalized coordinates known w.r.t. the world coordinate system positioned on the ground, and they are equal to the respective healthy trajectories of the four-segmented model introduced in Sec. 2.3.

- Hip forces \((F_{x_H}, F_{y_H})\) and segment lengths are as well ideally identical to the four-segmented healthy model from Sec. 2.3.

Firstly, we can express the CoM of each segment in generalized coordinates. It is important to underline that in Sec. 2.3 the kinematic chain of the four-segmented model has been computed from the bottom, i.e. starting from the ground, because the ankle trajectory was known from healthy gait data. In this section, the kinematic chain is instead derived from the top, i.e. starting from the hip joint, because hip and knee trajectories are assumed to be known for scaling purposes. For the sake of clarity, the symbols marked with a * indicate parameters that are related only to the prosthetic leg, while all the others are parameters that are assumed to be the same of the healthy
Appendix B. Dynamic Segmented Models of Human Body

leg.
\[ x_s^* = x_K + (l_s - d_s^*) \sin \theta_s \]
\[ y_s^* = y_K + (l_s - d_s^*) \cos \theta_s \]
\[ x_t^* = x_K - d_t^* \sin \theta_t \]
\[ y_t^* = y_K + d_t^* \cos \theta_t \] (B.1)

Secondly, Newton-Euler equations are written for each segment, according to the free body diagrams in Fig. B.1, along x, y, and around the CoM:

Prosthesis:
\[ F_{x_K}^* + F_{x_P}^* - m_s^* \ddot{x}_s^* = 0, \] (B.2)
\[ F_{y_K}^* + F_{y_P}^* - m_s^* (\ddot{y}_s^* + g) = 0, \] (B.3)
\[ \tau_s^* - I_s^* \ddot{\theta}_s + (x_s^* - x_P) F_{y_P}^* + (y_s^* - y_P) F_{x_P}^* + (x_K - x_s^*) F_{y_K}^* - (y_K - y_s^*) F_{x_K}^* = 0. \] (B.4)

Stump/Socket:
\[ F_{x_H} - F_{x_K}^* - m_t^* \ddot{x}_t^* = 0, \] (B.5)
\[ F_{y_H} - F_{y_K}^* - m_t^* (\ddot{y}_t^* + g) = 0, \] (B.6)
\[ \tau_t^* - I_t^* \ddot{\theta}_t + (x_t^* - x_K) F_{y_K}^* - (y_t^* - y_K) F_{x_K}^* + (x_H - x_t^*) F_{y_H} - (y_H - y_t^*) F_{x_H} = 0. \] (B.7)

Finally, solving the equations above we can find the scaled values of GRFs, i.e. \( F_{x_P}^*, F_{y_P}^* \), knee forces, i.e. \( F_{x_K}^*, F_{y_K}^* \), and knee and hip torques, i.e. \( \tau_s^*, \tau_t^*, \) that guarantee the same behaviour of the prosthetic leg compared to a human leg. Their extensive formulation can be found using the Matlab code C.1.2.3.

B.2 Models for Human Model Reference Adaptive Control

During a human gait cycle, stance phase and swing phase differ significantly in dynamic terms. A human leg during level ground walking in stance phase can be modelled by a double inverted pendulum, while in swing phase it can be modelled by a double pendulum. In the next two sections, the state space representations of the two idealized models for stance and swing phase are derived.

B.2.1 Stance Phase: Double Inverted Pendulum

The upper body, i.e. the HAT, the residual leg and the prosthesis of an amputee subject are modeled by two segments with a HAT mass, as shown in Fig. B.2.a. The segments are connected by one hinge joint (knee) and to the ground through a pivot point representing the foot. Center of mass and length of each segment are defined using anthropometric data [106]. The segment angles are defined w.r.t the vertical axis (see free body diagrams in Fig. B.2.b) and positive angles are counted counter clockwise. The world coordinate system is assumed to lie at the pivot point. The Newton-Euler method is used to derive the EoMs for the stance phase of a nominal gait cycle.
First, we can write the CoM position of each segment in generalized coordinates:

\[
\begin{align*}
x_s &= -d_s \sin \theta_s \\
y_s &= +d_s \cos \theta_s \\
x_t &= -d_t \sin \theta_t - l_s \sin \theta_s \\
y_t &= +d_t \cos \theta_t + l_s \cos \theta_s
\end{align*}
\] (B.8)

and the same can be done for the knee and hip joints:

\[
\begin{align*}
x_K &= -l_s \sin \theta_s \\
y_K &= +l_s \cos \theta_s \\
x_H &= -l_t \sin \theta_t - l_s \sin \theta_s \\
y_H &= +l_t \cos \theta_t + l_s \cos \theta_s
\end{align*}
\] (B.9)

Second, Newton-Euler equations are written for each segment (Fig. B.2.b) along x, y, and around the CoM:

**Shank:**

\[
\begin{align*}
F_{xK} + F_{xA} - m_s \ddot{x}_s &= 0, \\
F_{yK} + F_{yA} - m_s (\ddot{y}_s + g) &= 0, \\
\tau_K - I_s \ddot{\theta}_s + x_s F_{yA} + y_s F_{xA} + (x_K - x_s) F_{yK} - (y_K - y_s) F_{xK} &= 0.
\end{align*}
\] (B.10-12)

**Thigh:**

\[
\begin{align*}
-x_{xK} - m_t \ddot{x}_t - m_{hat} \ddot{x}_{hat} &= 0, \\
-F_{yK} - m_t (\ddot{y}_t + g) - m_{hat} (\ddot{y}_{hat} + g) &= 0, \\
-\tau_K - I_t \ddot{\theta}_t + (x_t - x_K) F_{yK} - (y_t - y_K) F_{xK} &= 0, \\
-(x_{hat} - x_t)(m_{hat} (\ddot{y}_{hat} + g)) + (y_{hat} - y_t)(m_{hat} \ddot{x}_{hat}) &= 0.
\end{align*}
\] (B.13-15)

Finally, we can derive the state space representation w.r.t the world coordinate system placed at the contact point between the leg and the ground. The state vector \( \mathbf{x} = [\theta_t; \theta_s; \ddot{\theta}_t; \ddot{\theta}_s] \subset \mathbb{R}^4 \) is defined by the angle and angular velocity of thigh and shank. The input to the system \( u = \tau_{mdl} \in \mathbb{R} \) is the knee torque. First we can write the nonlinear system as in Eq. (B.16):

\[
\begin{align*}
\dot{x} &= f(\mathbf{x}, u) \\
y &= g(\mathbf{x}, u)
\end{align*}
\] (B.16)

To obtain the state space representation, the system in Eq. (B.16) is linearized instantaneously
Figure B.1: Free body diagrams of a three-segmented model of an impaired subject walking during stance phase: a. HAT, b. stump/socket, c. prosthesis.
B.2. Models for Human Model Reference Adaptive Control

Figure B.2: (a) Double inverted pendulum model of a human leg in stance phase. (b) Free body diagrams of shank and thigh segments around the actual state $x^*$ and input $u^*$.

\[
A = \left. \frac{\partial f(x,u)}{\partial x} \right|_{x=x^*,u=u^*} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix} \quad (B.17)
\]

\[
B = \left. \frac{\partial f(x,u)}{\partial u} \right|_{x=x^*,u=u^*} = \begin{pmatrix} b_{11} \\ b_{21} \\ b_{31} \\ b_{41} \end{pmatrix} \quad (B.18)
\]

\[
C = \left. \frac{\partial g(x,u)}{\partial x} \right|_{x=x^*,u=u^*} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad (B.19)
\]

\[
D = \left. \frac{\partial g(x,u)}{\partial u} \right|_{x=x^*,u=u^*} = 0 \quad (B.20)
\]

For the matrix $A$, the coefficients

\[
a_{11} = a_{12} = a_{14} = a_{21} = a_{22} = a_{23} = 0, \quad (B.21)
\]

\[
a_{13} = a_{24} = 1, \quad (B.22)
\]

while to know the values of the other coefficients please check the Matlab script C.1.3.1 because they are too long and complex to be written. For control purposes only the matrix $B$ is used, thus
we specify only its coefficients.

\[ b_{11} = b_{21} = 0 \]  
\[ b_{31} = -(I_s + d_s^2m_s + l_{hat}^2m_{hat} + l_s^2m_t + l_t^2m_t \cos(\theta_s^* - \theta_t^*)) \]
\[ + l_s l_t m_{hat} \cos(\theta_s^* - \theta_t^*)/(I_s l_t + (d_t^2l_s^2m_t^2)/2) \]
\[ + (l_{hat}^2l_{hat}^2m_{hat}^2)/2 + I_s d_s^2m_s + I_s d_t^2m_t + I_{hat} l_{hat}^2m_{hat} \]
\[ + l_t l_{hat}^2m_{hat} - l_t l_{hat} l_{hat} (d_t^2l_s^2m_t^2 \cos(2\theta_s^* - 2\theta_t^*))/2 \]
\[ - (l_{hat}^2l_{hat}^2m_{hat}^2(2\theta_s^* - 2\theta_t^*))/2 + d_t^2d_t^2m_s m_t \]
\[ + d_t^2l_{hat}^2m_{hat} m_t + d_t^2l_{hat}^2m_{hat} m_t \]
\[ - d_t l_{hat} l_{hat} m_t m_t - d_t l_{hat} l_{hat} m_t m_t \cos(2\theta_s^* - 2\theta_t^*)) \]  
\[ b_{41} = (m_t d_t^2l_t + l_s m_{hat} \cos(\theta_s^* - \theta_t^*) d_t + m_{hat} l_t^2 l_t^2) \]
\[ + l_s m_{hat} \cos(\theta_s^* - \theta_t^*) l_t + I_t/(I_s l_t + (d_t^2l_s^2m_t^2)/2) \]
\[ + (l_{hat}^2l_{hat}^2m_{hat}^2)/2 + I_s d_s^2m_s + I_s d_t^2m_t + I_{hat} l_{hat}^2m_{hat} \]
\[ + l_t l_{hat}^2m_{hat} - l_t l_{hat} l_{hat} (d_t^2l_s^2m_t^2 \cos(2\theta_s^* - 2\theta_t^*))/2 \]
\[ - (l_{hat}^2l_{hat}^2m_{hat}^2(2\theta_s^* - 2\theta_t^*))/2 + d_t^2d_t^2m_s m_t \]
\[ + d_t^2l_{hat}^2m_{hat} m_t + d_t^2l_{hat}^2m_{hat} m_t \]
\[ - d_t l_{hat} l_{hat} m_t m_t - d_t l_{hat} l_{hat} m_t m_t \cos(2\theta_s^* - 2\theta_t^*)) \]  

We thus found the following linearized state space representation for the model plant:

\[ \dot{x}(t) = Ax(t) + Bu(t) \]  
\[ y(t) = Cx(t) \]

\section*{B.2.2 Swing Phase: Double Pendulum}

The leg is represented by two segments, i.e. the thigh and the shank, that are connected by a hinge joint, i.e. the knee. The thigh is connected to the rest of the body through a pivot point representing the hip joint (Fig. B.3.a). Center of Mass and length of each segment are defined using anthropometric data [106]. The segment angles are defined w.r.t the vertical axis (see free body diagrams in Fig. B.3.b) and positive angles are counted counter clockwise. The world coordinate system is assumed to lie at the hip pivot point. The Newton-Euler method is used to derive the EoMs for the swing phase of a nominal gait cycle.

First, we can write the CoM position of each segment in generalized coordinates:

\[ x_s = l_t \sin \theta_t + (l_s - d_s) \sin \theta_s \]
\[ y_s = -l_t \cos \theta_t - (l_s - d_s) \cos \theta_s \]
\[ x_t = (l_t - d_t) \sin \theta_t \]
\[ y_t = -(l_t - d_t) \cos \theta_t \]

and the same can be done for the knee joint:

\[ x_K = l_t \sin \theta_t \]
\[ y_K = -l_t \cos \theta_t \]
Second, Newton-Euler equations are written for each segment (Fig. B.3.b) along x, y, and around the CoM:

**Shank:**

\[
- F_{xK} - m_s \ddot{x}_s = 0, \quad \text{(B.30)}
\]

\[
- F_{yK} - m_s (\ddot{y}_s + g) = 0, \quad \text{(B.31)}
\]

\[
- \tau_K - I_s \ddot{\theta}_s - (x_K - x_s) F_{yK} + (y_K - y_s) F_{xK} = 0. \quad \text{(B.32)}
\]

**Thigh:**

\[
F_{xK} + F_{xH} - m_t \ddot{x}_t = 0, \quad \text{(B.33)}
\]

\[
F_{yK} + F_{yH} - m_t (\ddot{y}_t + g) = 0, \quad \text{(B.34)}
\]

\[
\tau_K - I_t \ddot{\theta}_t + (x_K - x_t) F_{yK} + (y_t - y_K) F_{xK} - x_t F_{yH} + y_t F_{xK} = 0. \quad \text{(B.35)}
\]

Finally, we can derive the state space representation w.r.t the world coordinate system placed at the hip joint. The state vector \( \mathbf{x} = [\theta_t; \theta_s; \dot{\theta}_t; \dot{\theta}_s] \in \mathbb{R}^4 \) is defined by the angle and angular velocity of thigh and shank. The input to the system \( u = \tau_{mdl} \in \mathbb{R} \) is the knee torque. First we can write the nonlinear system as in Eq. (B.36):

\[
\begin{align*}
\dot{\mathbf{x}} &= f(\mathbf{x},u) \\
\mathbf{y} &= g(\mathbf{x},u)
\end{align*} \quad \text{(B.36)}
\]

To obtain the state space representation, the system in Eq. (B.36) is linearized instantaneously around the actual state \( \mathbf{x}^* \) and input \( u^* \).

\[
A = \left. \frac{\partial f(\mathbf{x},u)}{\partial \mathbf{x}} \right|_{\mathbf{x}=\mathbf{x}^*,u=u^*} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix} \quad \text{(B.37)}
\]

\[
B = \left. \frac{\partial f(\mathbf{x},u)}{\partial u} \right|_{\mathbf{x}=\mathbf{x}^*,u=u^*} = \begin{pmatrix} b_{11} \\ b_{21} \\ b_{31} \\ b_{41} \end{pmatrix} \quad \text{(B.38)}
\]

\[
C = \left. \frac{\partial g(\mathbf{x},u)}{\partial \mathbf{x}} \right|_{\mathbf{x}=\mathbf{x}^*,u=u^*} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad \text{(B.39)}
\]

\[
D = \left. \frac{\partial g(\mathbf{x},u)}{\partial u} \right|_{\mathbf{x}=\mathbf{x}^*,u=u^*} = 0 \quad \text{(B.40)}
\]

For the matrix \( A \), the coefficients

\[
a_{11} = a_{12} = a_{14} = a_{21} = a_{22} = a_{23} = 0, \quad \text{(B.41)}
\]

\[
a_{13} = a_{24} = 1, \quad \text{(B.42)}
\]
Figure B.3: (a) Double pendulum model of a human leg in swing phase. (b) Free body diagrams of shank and thigh segments

while to know the values of the other coefficients please check the Matlab script C.1.3.2 because they are too long and complex to be written. For control purposes only the matrix $B$ is used, thus we specify only its coefficients.

$$b_{11} = b_{21} = 0 \quad \text{(B.43)}$$

$$b_{31} = (m_s d_s^2 - 2 m_s d_s l_s - l_s m_s \cos(\theta_s^* - \theta_t^*))d_s$$
$$+ m_s d_s^2 + l_s m_s \cos(\theta_s^* - \theta_t^*)l_s + l_s)/(I_s l_t$$
$$+ (d_s l_s^2 m_s^2)/2 + (l_s^2 l_t^2 m_s^2)/2 + I_s d_s^2 m_s + I_s d_s^2 m_t$$
$$+ I_s l_s^2 m_s + I_s l_s^2 m_t + I_s l_t^2 m_t - (d_s l_s^2 m_s^2 \cos(2\theta_s^*$$
$$- 2\theta_t^*)))/2 - (l_s l_t^2 m_s^2 \cos(2\theta_s^* - 2\theta_t^*))/2$$
$$+ d_s^2 d_s^2 m_s m_t - d_s l_t l_s^2 m_s^2 + d_s^2 d_s^2 m_t m_s + d_s l_t l_s^2 m_t m_t$$
$$+ l_s^2 m_s m_t - 2 l_s d_s d_s l_s m_s - 2 l_s d_s l_t m_s + d_s l_t l_s^2 m_s \cos(2\theta_s^* - 2\theta_t^*)$$
$$- 2 d_s d_s^2 l_s l_s m_s - 2 d_s d_s d_s l_s m_t - 2 d_s d_s l_s l_t m_t$$
$$- 2 d_s d_s^2 l_s l_t m_s + 4 d_s d_s l_s l_t m_t)$$

$$b_{41} = -(I_t + d_s^2 m_s + l_s^2 m_s + l_t^2 m_t - 2 d_s l_t m_t$$
$$- d_s l_t m_s \cos(\theta_s^* - \theta_t^*)$$
$$+ l_s l_s m_s \cos(\theta_s^* - \theta_t^*))/(I_s l_t + (d_s l_s^2 m_s)/2$$
$$+ (l_s^2 l_t^2 m_s^2)/2 + I_s d_s^2 m_s + I_s d_s^2 m_t + I_s l_s^2 m_s + I_s l_t^2 m_s$$
$$+ I_s l_t^2 m_t - (d_s l_s^2 m_s^2 \cos(2\theta_s^* - 2\theta_t^*))/2$$
$$- (l_s l_t^2 m_s^2 \cos(2\theta_s^* - 2\theta_t^*))/2 + d_s^2 d_s^2 m_s m_t$$
$$- d_s l_s l_t^2 m_s^2 + d_s^2 d_s^2 m_t m_t + d_s l_t l_s^2 m_s m_t + d_s l_t l_s^2 m_t m_t$$
$$- 2 l_s d_s d_s l_s m_s - 2 l_s d_s l_t m_s + d_s l_t l_s^2 m_s \cos(2\theta_s^*$$
$$- 2\theta_t^*) - 2 d_s d_s^2 l_s l_s m_s - 2 d_s d_s d_s l_s m_t - 2 d_s d_s l_s l_t m_t$$
$$- 2 d_s d_s^2 l_s l_t m_s + 4 d_s d_s l_s l_t m_t) \quad \text{(B.45)}$$

The state space representation for the swing phase model is the same as the one for stance phase presented in Appendix B.26 (Eq. (B.26)), only with different $A$ and $B$ matrices.
Appendix C

Matlab Code and Data

C.1 Matlab Code

C.1.1 Inverse Dynamics

1. Four-segmented model dynamics of healthy subject:
   \textit{Matlab/InverseDynamics/InverseLeg.m}

2. Three-segmented model dynamics of impaired subject with prosthesis:
   \textit{Matlab/InverseDynamics/InverseProsthesis.m}

3. Healthy inverse dynamics using Pfeifer’s gait data:
   \textit{Matlab/InverseDynamics/ComputeHealthyTorques.m}

C.1.2 Impedance Scaling

1. Four-segmented model dynamics of sound leg:
   \textit{Matlab/Scaling/InverseLeg.m}

2. Three-segmented model dynamics of impaired subject with prosthesis:
   \textit{Matlab/Scaling/InverseProsthesis_ChangeThip.m}

3. Impedance scaling derivation:
   \textit{Matlab/Scaling/FindScaling.m}

4. Plot scaling results on joint torques and GRFs:
   \textit{Matlab/Scaling/AlgebraicallyEvaluate_MotionChangeThip.m}

C.1.3 HMRAC Models and Reference Trajectory

1. Stance phase model:
   \textit{Matlab/AdaptationLaw/StancePhase/FindStateSpace.m}

2. Swing phase model:
   \textit{Matlab/AdaptationLaw/SwingPhase/FindStateSpace_Swing.m}
Appendix C. Matlab Code and Data

3. Reference trajectory generation:
   Matlab/TrajectoryGeneration/GenerateKneeTrajectory.m

C.1.4 Forward Simulations

1. Forward simulation to evaluate NMS stability:
   Matlab/NMS_Forward_Simulation/forward_simulation.m

2. Forward simulation to evaluate HMRAC performance:
   Matlab/HMRAC_Forward_Simulation/HMRAC_evaluate.m

C.2 Data

The data used for the results of this thesis are included in the following folders:

1. NMS versus BK impedance comparison:
   RR: Data/NMSvsBK

2. HMRAC preliminary experiment for sinusoid tracking:
   RR: Data/HMRAC_SinusoidExperimentalTest

3. CLME-based BK adaptive impedance control:
   RR: Data/CLME_BK_AdaptTest_RR; AP: Data/CLME_BK_AdaptTest_AP; SB: Data/CLME_BK_AdaptTest_SB

4. State Machine-based BK adaptive impedance control:
   RR: Data/State_BK_AdaptTest_RR; AP: Data/State_BK_AdaptTest_AP; SB: Data/State_BK_AdaptTest_SB

5. State Machine-based NMS1 adaptive impedance control:
   RR: Data/State_NMS_AdaptTest_RR; AP: Data/State_NMS_AdaptTest_AP; SB: Data/State_NMS_AdaptTest_SB

6. State Machine-based NMS2 adaptive impedance control:
   RR: Data/State_NMS_AdaptTest_RR_new
Bibliography


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