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Reactive balance control of an active lower limb orthosis during perturbed walking

TFE22-148 - Rehab robotics

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Abstract

At present, gait assistance technologies are in constant development. Indeed, with the global ageing of world population and the increasing rate of deaths related to falls, there is an increasing need for locomotion assistance devices. Because lack of balance and walking impairments are among the most common causes leading to falls, more and more active lower limb orthoses are being commercialized to cope with gait disorders.

In spite of the global demand, specific reactive balance assistance that can respond to unexpected perturbations is rarely the subject of research for such devices. Therefore, we worked on the adaptation of potential balance models for an implementation in a mid-level controller of a lower limb orthosis.

First, we had to find a bio-inspired model describing efficiently the reactive balance behavior responses of lower limb joints during perturbed walking. We decided to go for a center of mass and a joints based kinematics model. Second, to assess the different performances and choose the most adapted model, we fitted the different models via a linear regression on experimental data and evaluated the different results. Based on the performances, we chose a model and a joint to act on, in order to test a model-based controller in a neuromuscular bipedal locomotion simulation with reduced reactive balance capacities.

Via the model fitting, we confirmed the ability of a delayed center of mass feedback model to reconstruct deviated ankle joints in response to a sagittal perturbation for different speeds of walking and different amplitudes of perturbation at a discrete time instance. Moreover, the evaluated models gave us more insights about neuromuscular sensorimotor transformations underlying reactive balance behavior of lower limb joints. Finally, the neuromuscular model did not allow us to assess the efficiency of our model, to enhance reactive balance through simulation on a rigid body, due to input and optimisation constraints.

By following a bio-inspired approach, we proposed a potential ankle joint orthosis controller providing the reactive balance assistance, which could be one of future key components in the rehabilitation area to reduce the increasing fall rates.

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Introduction

Nowadays, falls are a worldwide issue in terms of their impact on the general population's health but also with regard to the funding of the health system. Indeed, according to the Centers for Disease Control and Prevention (CDC), fall-induced death in the USA increased by 30% between 2007 to 2016. Furthermore, the CDC predicted a rate of seven deaths per hour for 2030 [1]. Besides death, falls can lead to serious irreversible injuries such as hip fractures or traumatic brain injuries [2] [3]. Moreover, the financial impact linked to falls can be tremendous with medical cost rising up to $50 billion per year [4]. With these day's global population levels of growth and ongoing health sciences improvements, life expectancy is continuously increasing, with the likely result that this matter is not about to fade away. One of the main risk factors, particularly among the elderly, is an inhibited balance capacity leading to gait disorders [5]. Apart from the natural fact of body ageing, numerous pathologies or events can lead into body equilibrium impairments such as strokes (cerebrovascular accidents, CVA) or amputations [6] [7] [8]. Therefore, there is a major need to develop and validate pharmaceutical and technological solutions to enhance balance to reduce the worldwide impact of falls.

The reduced balance ability is often a long-term secondary effect, which is not necessarily reversible. Therefore, more and more assistive devices have been developed to provide balance assistance. A common example are canes and walkers, which are a simple solution to improve equilibrium and locomotion of the user. However, Hamid *et al.* showed that the use of canes and walkers, demanded sometimes, high strength leading to high metabolic costs [9]. Therefore, a solution to cope with these drawbacks, would be an assistive device improving the balance of the user by providing the needed forces to reach an enhanced equilibrium. An assisting device responding to these criteria are lower limb active orthoses. Indeed, orthoses are assistive devices aiming to improve the locomotion ability of the wearer by powering one or more lower limb joints. The term "active" is defined by its ability to actively control the different powered joints [10]. Therefore, an active control of the joints provided by a lower limb orthosis could be a solution to infer balance assistance. In this regard, it is worth noting that there is a constant increase of commercialized active orthoses.

However, the vast majority of orthoses are mostly intended to assist in the locomotion without necessarily aiding during an unexpected loss of balance. The aim of this thesis is precisely to fill this void by proposing a mid-level bio-inspired controller that provides balance assistance following an unexpected perturbation. Indeed, most of the falls in elderly people occur after an unexpected trip or slip [11]. The goal of the controller will be to provide the necessary power to the torques to reach as close as possible a healthy reactive balance.

To reach our objective, we first reviewed the already existing models aiming at ensuring balance during perturbed walking, in order to adapt or study, the most appropriate one for future orthosis control implementation. Afterwards, we fitted the two chosen models, responding to our criteria, on experimental data to assess their ability to reconstruct healthy reactive balance moments behaviors. Thanks to the chosen models, we had the opportunity to discuss the sensorimotor transformation underlying the characteristic balance responses of each joint. Finally, we evaluated our controller's efficiency on a neuromuscular bipedal locomotion model with reduced reactive balance abilities.

The structure of this thesis is divided in three distinct parts: the first one aiming at giving an overview of different balance concepts. The second one looks at fitting two different models to experimental reactive healthy balance joint adjustments and the third one is focused on the assessment of our controller in a bipedal locomotion simulation.

Chapter 1

Context

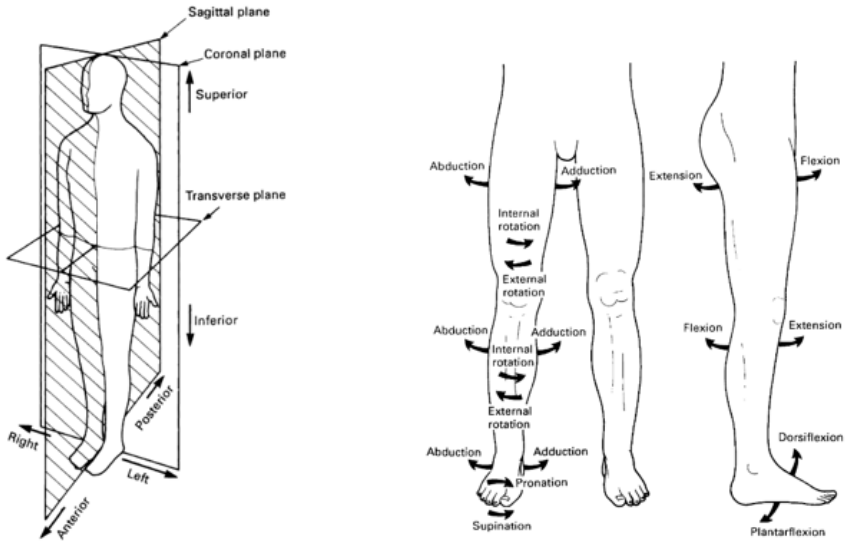
This introductory chapter provides the necessary context to allow the understanding of the thesis and realize how it answers to an existing scientific gap. It will be presented as a funnel description, beginning with a broad description of human locomotion followed by a detailed explanation of balance control in lower limb joints as well as some pathological balance patterns, and finally showcasing some existing lower limb orthoses balance controllers.

1.1 Human locomotion

1.1.1 Lower limb joint anatomical terms

To explain thoroughly the human locomotor system, we will begin this section by stating some important anatomical facts involving the lower limb joints to be studied: the ankle, the knee and the hip.

In the medical area, some anatomical positions have been defined to describe the movements of the lower extremities of the body. Therefore to represent body parts in space, three planes have been established: the sagittal, the coronal (frontal) and the transverse (horizontal). Moreover, according to those planes and in order to have a more precise description of the body movements, six directions have been established: the right/left direction in the sagittal plane, the anterior/posterior in the coronal plane and the superior/inferior in the transverse plane[12]. A visual aid of these anatomical positions and planes are represented in Figure 1.1a. In addition to these reference planes that allow the description of limb movements, it is important to state that joints, the interface between bones, permit motion of skeletal structures and therefore locomotion of the entire body [13]. Consequently, it is interesting to analyse how joints move according to each other. For the lower limb, the movements that are feasible throughout the different joints are summarized in Figure 1.1b. Moreover, a nice visual representation of the motion of the joints according to the entire body and to the muscles is shown in Appendix A.1. In the framework of this thesis, we will arbitrarily focus on the motion in the sagittal plane and hence on flexion and extension actions (called plantarflexion and dorsiflexion respectively for the ankle). Indeed, sagittal plane muscles are the first to induce joint motion during gait and to ease forward progression [14].
Another important structure for lower limb joints are the muscles. Indeed, they are the main engines of body locomotion, powered by the contraction of their fibers [15]. As



a) b)

Figure 1.1: a) - Anatomical positions with the three planes and the six directions, b) - Major lower limb joint feasible movements [12].

a matter of fact, the moment delivered by each joint constitutes mostly the sum of all internal moments produced by the surrounding muscles[16]. Thus, depending on the joint, different muscles will contribute for the generated torque. Prominent muscles of each joint are showed in Appendix A.2. For the ankle joint, the gastrocnemius (GAS) and the soleus (SOL) are the two muscles involved in plantarflexion motion while the tibialis anterior (TA) act during the dorsiflexion and the inversion of the foot. For the knee, the vastus (VAS) is solicited during extension motion and the hamstrings (HAM) act for the flexion. For the hip, the hip flexors (HFL) act for the flexion and the gluteus (GLU) for the extension [18]. These seven muscles will be the ones of the seven Hill-type muscles used in the studied neuromuscular bipedal locomotion model that will be presented in Chapter 3.

1.1.2 Gait cycle

The action of walking has the particularity to be a cyclic event. Through repetitive steps, we manage to move our body in space and toward arbitrary directions. Therefore, to describe efficiently human locomotion, the term "gait cycle/stride" has been introduced. Typical cycles, are divided in different levels, as illustrated in Figure 1.2. For humans, each leg is in the opposite phase of the cycle with respect to the other leg. On that account, the description of the gait cycle is done for one limb as reference.

The first level of division of the gait cycle is named the gait period, which is divided in two phases: swing and stance. Each phase can be distinguished trivially by following the foot behavior with respect to the ground. Indeed, the stance leg is represented by all the period during which the foot is in contact with the floor whereas the swing leg corresponds to the "flying" period of the foot during which it does not touch the floor[20].

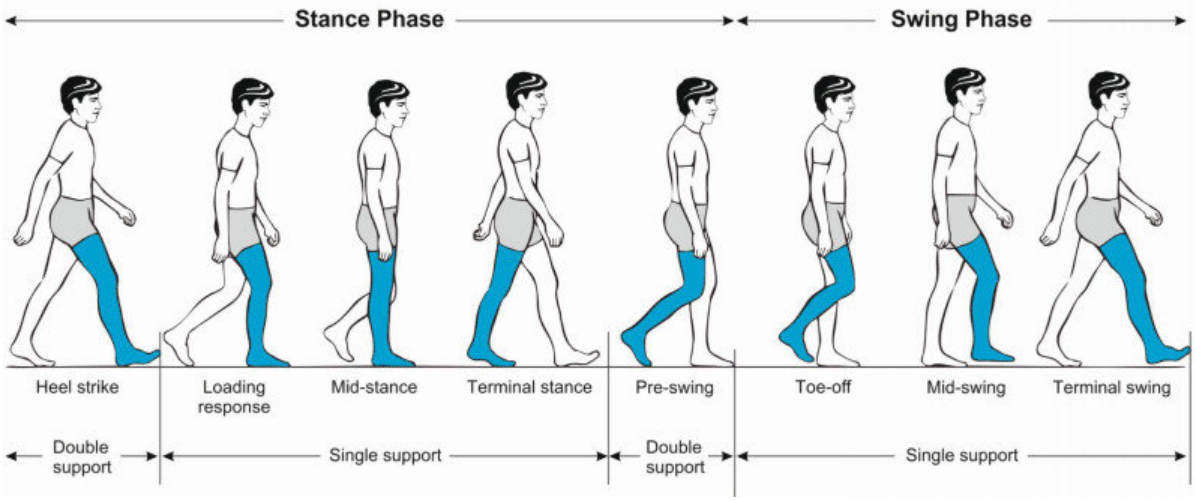


Figure 1.2: Overview of the gait cycle with the limb of reference in blue [19].

During one stride, the stance phase represents approximately 60% of the cycle while the swing phase represents 40% [21]. The second level of division corresponds to single and double support periods, which, as the names indicate, are differentiated by the fact that one or two feet are in contact with the ground. As we can observe in Figure 1.2, the stance phase is denoted by alternating double and single support times while, in contrast, the swing phase is characterized by a unique single support phase.

Finally, the third level of division dissects each phase of the first and second level according to the lower limb placement in space, in three different tasks: the weight acceptance, the single limb support and the limb advancement task [22]. A visual aid is given in Appendix B.1.

During the stance period, we have the weight acceptance task in which we have a transfer of the body weight to the leg that just finished swinging forward. This task is divided in two steps: in the first place, there is the heel strike (HS), which is the initial contact of the heel of the reference limb with the ground, additionally it is also the first double support period in stance. The primary goal of the HS is to have a full extension of the knee joint and to arrange the entire limb for step [23]. Afterwards, there is the loading response (LR), where the effective body weight transfer to the forward limb occurs. For the second task, we enter in the single limb support of the stance phase. During this task the reference limb will have to support the entire body weight while the other limb is lifted for the swing period. This task is also divided in two steps: the mid-stance (MS) during which the reference limb is going to move ahead based on a stationary foot and the terminal stance (TS) during which the heel of the reference foot is going to rise, moving the limb forward on the forefoot. The last task of the gait cycle is the limb advancement which contains the last step of the stance phase and the entire swing phase. This task is characterized by the lifting of the reference limb and by the preparatory behavior towards the next stance period. Four different steps can be distinguished. First, in the stance phase, we have the pre-swing (PS) where an increasing flexion of the ankle allows an unloading of the reference limb and a transfer of the body weight up to the other leg.

During swing, we enter in toe-off (TO), where the reference limb is going to be lifted and advanced along walking direction. Afterwards, the mid-swing (MS) step comes, where the reference limb, which was in a posterior position relative to the body trunk, is going to move forward and become anterior to the body. Finally this cyclic stride, ends with the terminal swing (TS) during which the reference limb finishes its advancement by preparing the contact of its heel with the floor and goes back to heel strike step to begin a new stride.

1.2 Balance control mechanisms during gait

In order to maintain balance, the human body uses several mechanisms to avoid falls. Whether it is during quiet stance or during steady state walking, the locomotor system has to cope with various constraints such as the human body particular anatomy or external perturbations.

1.2.1 Balance control during walking

1.2.1.1 Balance

Balance hazards can arise from many different sources that can be internal or external to the human body. In order to counteract these different instabilities, a constant neuromuscular control system has to act, to prevent falling. Indeed, sustaining balance is a neural control problem [24]. A generic term to formalize the control of the nervous system towards body equilibrium is postural control. It can be defined as "the act of maintaining, achieving or restoring a state of balance during any posture or activity" [25], whereas balance can be defined as "a generic term describing the dynamics of body posture to prevent falling" [26].

1.2.1.2 Involved sensory systems

When it comes to balance control, the nervous system, and more particularly, three sensory systems are going to be solicited: the vision, the vestibular and the somatosensory systems. In fact, thanks to the visual information, our body is able to avoid dangerous obstacles that could lead to a fall and plan our gait in an anticipatory manner. In addition, the vestibular system allows sensing our own balance state by relaying information about the linear and angular acceleration of the body [27]. Finally, the somatosensory system can be assimilated to a gathering of sensors and pathways, which react to kinematic modifications but also sense the contact with external objects, like the ground. This last structure provides the brain with spatial information, as well as with the position and velocity of the body segments, which will trigger the proper motor complexes to maintain functional postural balance [28].

1.2.1.3 Balance tasks

In scientific literature, balance control strategies have been widely studied for quiet standing, unlike walking, for which the underlying processes are not fully understood. Yet, scientific studies have shown that falls in the elderly occur mostly during walking, supporting the importance to extend the researches about balance during locomotion[29].

Indeed, balance tasks differ from a static situation to a dynamic situation, where we keep compensating constant little falls[30]. For standing and sitting (static), the objective is to keep the center of mass within the base of support (BOS [1]) of the body which is efficiently fulfilled by ankle actuators. However, during locomotion, there is a constant movement of the center of mass and of the base of support, implying a different balance strategy to keep the center of mass in an equilibrium position.

1.2.1.4 Dynamic balance control

During steady state walking of a healthy person, balance risks are the ones induced by the unstable human biomechanical anatomy. Indeed, 2/3 of our body weight is located in the upper part of our body, particularly in the head, the arms and the trunk (HAT), creating an upper body instability. A neuromuscular intervention is essential to ensure an efficient body mass distribution [26]. Additionally, our bipedal locomotor pattern, consists of two single limb support phases which enhance the weight transfer between the limbs but also bring a medio-lateral instability. To cope with these inherent challenges, counterbalancing moments are generated around the hip and the trunk, to stabilize the center-of-mass around an equilibrium position, therefore avoiding falls by preventing injuries [29].

1.2.1.5 Proactive and reactive balance control

In an environment where external risks are non-existent, balance impairments arise from the body anatomy itself or from a pathological behavior. To study how the nervous system would manage these extrinsic threats, balance control mechanisms during walking have been divided in two categories [32]. In the first category, we have the proactive balance control, that works in an anticipatory manner, before encountering the balance hazard. This type of control is characterized by two modes of functioning: the first mode is the generation of continuous torques via muscular excitation to counteract intrinsic anatomical challenges presented in the section 1.2.1.4 whereas the second mode is the adjustment of the posture and of the locomotion to avoid a detected external environmental threat. In the second category, we have the reactive control which refers to the automatic postural response to an undetected extrinsic danger, to attend restoring balance and avoid falling.

1.2.2 Reactive balance control

Reactive balance control seems to be the result of the sum of the synchronized lower limb torques to maintain equilibrium stemming from muscular activation [48]. This type of control strongly depends on the perturbation properties, from its onset timing to its plane of action.

1.2.2.1 Strategies

In this thesis, we will arbitrarily focus on the reactive balance control, but more in-depth information about proactive control can be found in the following articles [32] - [38]. In

[1] *"It is the area defined by the parts of the body and assistive devices that are in contact with the supporting surface"* [31]

order to detect the extend of the external perturbations, that has not been detected in an anticipatory manner, sensory systems will be solicited for the initiation of the appropriate postural response. For the reactive balance, three different strategies have been described in scientific literature:

1. **Ankle strategy**: This first method consists in a modulation of the position of the center of pressure (CoP)[2] of the stance limb through a delayed activation from distal to proximal lower limb muscles: ankle plantar/dorsi-flexor, knee flexor/extensors and hip flexors/extensors, generating different joints torques [39]. This method restores the center of mass equilibrium trajectory and is generally preferred for slow and low perturbations [40][41].

2. **Hip strategy**: For this postural response, the different body segments are going to counter-rotate around the axis of the COM to reduce the angular moment brought by the external perturbation. Contrary to the ankle strategy, there is a proximal to distal activation of the hip flexors followed by the knee extensors. This strategy is preferred over the other ones when the perturbation is fast or of higher amplitudes[39].

3. **Stepping strategy**: This last strategy aims at fine tuning different muscular activity, in order to adjust foot placement to take a step, to establish a new base of support and stabilize the body [42]. This strategy is generally preferred for higher perturbation amplitudes.

Often, the reactive balance behavior, in response to an unexpected alteration, is a mix between these different strategies [43].

1.2.2.2 Phase-dependent reflex modulation

LM. Nashner has been a pioneer researcher in the study of perturbed balance control walking behaviors. One of its particularly interesting findings are the phase-dependent reflex modulation [46]. Indeed, it seems that depending on the phase in which the perturbation onset occurs, the muscular pattern, behind the postural responses, differ. Tang *et al.*, studied the proximal and distal muscular responses following a slip disturbance. They showed that depending on the phase, postural responses followed significantly different behaviors[47].

1.2.2.3 Perturbation dependent strategy modulation

Recent studies have shown that depending on the plane of actuation of the perturbation, the preferred balance control strategy would differ. For instance, for a coronal plane perturbation the preferred postural response seems to be mainly the stepping strategy [49] - [51]. Whereas for a sagittal plane perturbation, the body seems to rely on both stepping and ankle strategies to regain a stable balance[52]-[54].

[2]Center of pressure (COP) is the point of location of the vertical ground reaction force vector [44]. The ground reaction force vector represents the sum of all forces acting between a physical object and its supporting surface. [45]

1.3 Pathological balance

Balance impairments can arise from many different pathological origins. Indeed, it has been shown in section 1.2, that balance control is a neural control problem that will trigger muscle activation in order to stabilize equilibrium loss. These pathological sources have been classified in four categories: functional deformity, muscle weakness, impaired control and pain [55]. Therefore, from a brain damage to a limb loss, the solution to aid such patients for the rehabilitation of their balance disorders could be similar. Nowadays, the development of balance controllers for assistive devices is not broadly studied, while a large part of the population could benefit from it. In order to have a representative sample of balance impairments subjects, we will present stroke, trans-femoral amputee and aged patients equilibrium disorders.

1.3.1 Stroke patients

A stroke, also called cerebrovascular accident (CVA), is characterized by a local loss of brain function due to vascular supply interruption [56]. This disease has a worldwide impact with an incidence of 12.2 million per year according to the World Stroke Organisation (WSO) and an incidence of 52 CVA per day in Belgium [57] [58]. Unfortunately, this disease can be lethal and survivors often present long-term limitations as partial or complete motor loss leading to walking dysfunctions [59][60]. One particular constraint encouraging this dysfunctional gait, is patients' reduced balance control ability [61]. Indeed, an inhibited muscular efficiency, leads to lower joint torque implying a lower counteracting force against falls. In addition, recovering a completely functional gait, is one of the most cited goals of post-stroke patients [62]. Therefore, the rehabilitation of walking balance in stroke patients is of major importance and already led to the development of specific assistive gait devices. For instance, Tyson, S. F. *et al*, proposed the use of an ankle foot orthosis to enhance gait and balance of post-stroke patients. They demonstrated that the orthosis led to an improvement of certain aspects of locomotion and equilibrium [63].

1.3.2 Trans-femoral amputee patients

A trans-femoral amputee (TFA) is a patient presenting a lower limb amputation at or above the knee joint [64]. Approximately, more than 36 million persons live with a lower limb amputation and 26% of these amputations are trans-femoral [65]. With the absence of one of the limbs of support, the prosthetic is essential to allow the autonomous upright locomotion of the TFA subject. A wide panel of prosthetic are developed for lower limb amputees in order to replace the missing limb. A more surprising technology has been investigated by Sanz-Morere, C. B. *et al.*, by creating a knee-ankle-foot orthosis for the sound limb to help compensating the additional mechanical constraints stemming from the amputation [66]. In order to assess walking impairments, Lamoth, C. J. *et al.*, analyzed TFA's gait wearing a prosthetic and found some walking limitations notably a reduced balance control[67]. Consequently, this shows a need of balance control in already existing trans-femoral gait assistive devices to cope with this default.

1.3.3 Aged patients

Nowadays, we are facing a major problem that affects us all: the global ageing of the population. Indeed, in 2021, more than 700 million people in the world were older than 65 years old [68]. Older adults, show higher risks of falling and thus, of injuries, arising the need for adequate technology to avoid this kind of events [69]. Several authors have shown that balance ability declines with age [70] [71]. The main causes can be wrapped up by age related motor, cognitive and sensory systems modulations [72]. As the effects of ageing are inevitable, the development of assistive devices to reduce falls has already emerged. For instance, different foot orthoses have been created to enhance the balance of elderly people and it has been shown that they could efficiently improve their control[73] [74].

1.4 Lower limb orthoses balance controllers

The global objective to reach throughout the thesis, is to find, adapt or design a reactive balance controller that could be implemented, in the future, in a lower limb orthosis[3]. According to the standard, ISO 8549: *"An orthosis is an externally applied device used to influence the structural and functional characteristics of the neuromuscular and skeletal system"* [76]. This section aims at giving a general classification of lower limb assistive controllers and at reviewing existing balance controllers.

1.4.1 Controller

A controller is a unit in a complete control system that is going to minimize the deviation between an actual measured signal and a target [77]. Baud *et al.*, proposed a classification for lower limb gait assistive controllers based on their function in the hierarchy of the control system [78]. This categorization is divided in three main levels and is summarized in Appendix C.1: the high, the mid and low-level controls. First, we have the high-level control which is responsible for the general operation mode of the orthoses. Second, we have the mid-level control which is the most studied one in scientific literature. Within this layer, there is the detection block that has the objective to approximate the gait phase (0 to 100%) or gait states (eg. gait periods, support phases or tasks) via external inputs (eg. sensors). Moreover, there is the action block, that often takes the detection block output as input, to compute a motor action as joint angles or force torques. Finally, there is the low-level control which can be assimilated to the workers of a company that are going to produce a certain action under the supervision of the above levels. For instance,if the action block of the mid-level layer has computed a torque as output, the low-level controller is going to generate this motor action by initiating the actuators of the device. For our purpose, the implementation of a reactive balance controller would lay in the mid-level layer, in the action sub-block.

[3] *"In general, the term 'exoskeleton' is used to describe a device that augments the performance of an able-bodied wearer, whereas the term 'orthosis' is typically used to describe a device that is used to assist a person with a limb pathology"* [75]. Both are often interchangeably used in literature.

1.4.2 Review of some balance assistive controllers for lower limb powered orthoses

Different mid-level lower limb active orthoses controllers, intended for balance assistive strategies, have been detailed in scientific literature [78] [79]. Hereunder, we present some of the main categories:

1. **Model-computed action to keep balance (BAL)**: This class of controller uses mathematical models of gait in order to provide a balance assistance. A first example, has been implemented in the MINDWALKER, a multi-joint exoskeleton, where hip adduction and abduction were provided using the notion of extrapolated center of mass, to ensure a proactive balance [80]. Another team used this type of control to also enhance proactive balance of a lower limb orthosis, by applying assistive torques based on a model taking the weighted sum of gravity, coriolis and inertial terms, as inputs [81]. Some recent research, tried to model the ankle strategy via a linear combination of the delayed deviation of the COM kinematics to predict the needed torque for a healthy reactive balance subject [82]. This last model will be widely discussed in Chapter 2. A more recent controller has been implemented in a powered ankle-foot orthosis for reactive balance control via a linear combination of the body sway angle [83].

2. **Neuromuscular model (NMM)**: This second type of controllers aims at mimicking the human neuromuscular structure. To do so, the generated output joint torques are computed based on virtual muscles. For example, Hill-type virtual muscles are a simple mechanical model broadly employed in locomotion computer models, represented in Figure 1.3 [84]. This model gives an efficient simplified representation of the factors influencing the amount of force produced by a real human muscle. The contractile element (CC) represents the "active" force of the

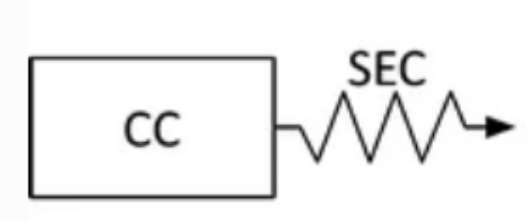


Figure 1.3: Hill muscle model where CC is the contractile component in series with an elastic component SEC [84]

muscle produced by its contraction in response to a nervous excitation. The series elastic component (SEC), acts as a spring to store elastic energy during the stretching of a muscle [85]. Thanks to this kind of simplified model, various adapted neuromuscular models of gait have birthed. Making NMM a class of bio-inspired controllers.

Some controllers, use predefined trajectories of gait from healthy subjects to control the torques behavior generated by the orthosis. The limits of such a controller is its lack of malleability with regard to the user, by sometimes imposing unnecessary motions. NMM models cope with this drawback by ensuring a follow up of the

motion of the different segments of the wearer and adapt its behavior in consequence and discard extrinsic risks. One of the defaults of neuromuscular based controllers are their tedious implementation and high number of parameters to tune.

In scientific literature, a NMM controller for lower limb prosthesis has been studied, where a balance recovery controller based on the global function of the leg in balance, has been explored [86] [87]. Moreover, some promising controllers for future orthotic implementation, based on COM feedback control combined with reflex-based neuromuscular model, are being currently assessed [88][89].

3. **Adaptive oscillators (AOs)-based control**: Another interesting class of controller is the one based on adaptive oscillators. It is a control that has the ability to adapt its oscillator parameters (eg. frequency) to learn the frequency of any periodic input signal [90]. This kind of method is relatively useful for cyclic motion, as for walking, but seems less adaptable for situations like unexpected perturbations. However, AOs controllers could be useful for detection purposes. Indeed, Monaco *et al.*, used adaptive oscillators to detect balance loss and initiate the balance recovery response, provided by torques via an active pelvis orthosis[91].

Chapter 2

Model fitting

This chapter aims at discussing the ability of two different feedback delayed control models to reconstruct lower limb joint moments adjustments in response to forward and backward perturbed walking.

2.1 Introduction

The objective of this thesis is to study, adapt or design a mid-level controller for lower limb joints orthoses, actuating in the sagittal plane and bringing reactive balance assistance, after a sagittal plane perturbation.

The first step was to find an appropriate model that would mimic efficiently the reactive balance behavior of one or more lower limb joints. Moreover, we had a specific interest in finding a bio-inspired controller, meaning that the provided balance assistance would stem from human-like principles[92]. First, we found that during a sagittal plane perturbation, the preferred reactive balance strategies were both stepping and ankle strategies. To narrow the results of our research, we decided arbitrarily to focus on the ankle strategy, where the flexors and extensors of our three joints of interest are involved.

By reviewing different controllers in scientific literature, we found a promising model responding to our criteria of research. Indeed, Afschrift *et al.* proposed a model, based on delayed feedback of COM kinematics, able to reconstruct ankle deviations in response to saggital perturbations[82]. Additionally, they proposed an equivalent model where center-of-mass feedback predicted the muscular activation pattern during reactive balance. This model stems from bio-inspired principles of sensorimotor transformations underlying human balance control.

For this thesis matter, we decided to focus on the direct relationship predicting the joint torque. Indeed, orthoses being an external device, an electromyographical follow-up would be tedious. Based on the article's results, the COM delayed feedback model could be a potential reactive balance assistance controller where balance would be provided in a human-like manner.

The goal of this chapter was two folded: on the one hand, the reproduction of Afschrift *et al.* results to validate their conclusions for the ankle and on the other hand,

to show if this model could fit other limb joints behavior during the ankle strategy. In order to provide more insights towards underlying neural control phenomenons, we also evaluated a joint kinematics based controller, as proposed in the article.

2.2 Methods

Our methodology, to meet our different objectives, was similar to the one followed in Afschrift *et al.* article.

2.2.1 Experimental data

To begin with, we needed an experimental data base of healthy subjects, undergoing sagittal plane perturbations, to assess the quality of the model fits. The data base had to include joints and COM kinematics recorded during unperturbed and perturbed walking. In the article, three data bases responded to our needs. By following the advise of Mr. Maarten Afschrift, we decided to use a data set where a discrete pelvis perturbation was applied during steady walking [93]. Indeed, as the perturbation is located close to the center of mass, the results seem to be the most assessable.

For this experiment, nine young healthy subjects (age 25 $\pm$ 2 std years) were gathered in order to apply anterior-posterior (AP, forward and backward in the sagittal plane) and medio-lateral (ML, forward and backward in the coronal plane) pelvis perturbations of 150 $[ms]$ at right toe off, for four different magnitudes (cf. Figure 2.1) at two different walking speeds (0.62 and 1.25 $[m/s]$). For the features of the subjects, joint kinematics

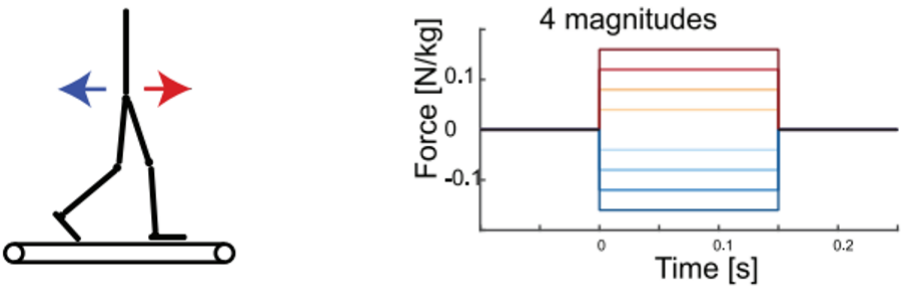


Figure 2.1: Overview of discrete pelvis push data set [82],[93].

were obtained with inverse dynamic tools while COM positions and velocities where derived from joints kinematics and a musculoskeletal model provided by the open-source software, OpenSim v3.3 [94]. A more detailed description of the data is provided in the article [93]. We limited our study to the AP perturbations and to the motion of our three joints of interest in the sagittal plane (flexion and extension) for the stance leg as the CoP modulation during the ankle strategy needs ground support. For our work, all data was processed using Matlab (R2021a, Mathworks).

2.2.2 Feedback delayed models

With the aim of providing a comparative study, two models will be discussed in this chapter. We chose the models presented in Afschrift *et al.* article: the COM feedback model and the local joint feedback model. An advantage of both models, is that their inputs are easily measurable, making them potential candidates for an eased implementation in assistive gait devices. These two models have not been chosen randomly, indeed they were selected to test the hypothesis of whether the reactive balance during walking had a task-level feedback (COM) or a local reflex based feedback control. In other words, it allows to evaluate if joints responses to perturbation are modulated by the central nervous system to recover balance (COM = task variable) or if they are produced from local stretch reflexes to recover the initial posture of the limb, without necessarily contributing to the task goal [95]. Another bio-inspired asset of these models, is the fact that each of their inputs is delayed by a neuronal time, representing the time needed for signal transmission and processing between the joints and the corresponding nervous complex.

2.2.2.1 COM feedback model

Previous works have shown that during perturbed standing, the joints torques and the different muscles activities could be described by a COM feedback model [52] [96] [97]. In Afschrift *et al.* article, they tested if it was also the case for walking. In Chapter 1, we have seen that the body balance task was intrinsically linked to the center of mass, to ensure equilibrium. Thus, we are going to test the ability of the following relationship (eq. 2.1), taking delayed COM kinematics as inputs, to explain experimental data. However, this equation is also going to give us information about the potential task-level feedback control of the reactive joint responses.

$$\Delta T_{COM}(t) = K_p(s)\Delta COM(t-\tau) + K_v(s)\Delta \dot{COM}(t-\tau) \tag{2.1}$$

In this equation $\Delta T_{COM}(t)$ is the deviation of joint moment from the unperturbed trajectory, K_p and K_v are feedback gains dependent of the phase in the gait cycle (s), $\Delta COM(t-\tau)$ and $\dot{COM}(t-\tau)$ denote the difference between the perturbed and unperturbed center of mass position and velocity respectively and t the time. The neural delay is represented by τ and was based on a sensitivity analysis for each joint explained in section 2.2.5, but was initially set at $\tau = 100\ [ms]$ for every joint. By following the categorization of lower limb powered orthoses controllers of section 1.4.2 of Chapter 1, we can classify this model in the computed action to keep balance (BAL) models. Thanks to this model, neural relations underlying reactive balance could be understood and allow human-like balance assistance for future orthoses by applying corrective joint torques.

2.2.2.2 Local joint feedback model

The alternative model, used as comparative support for our model of interest, is the delayed local joint feedback model. This comparative study is going to give us more insights about the underlying control of lower limb joints during the reactive balance. Indeed, this model takes joint kinematics as inputs and it can be modelled by equation 2.2.

$$\Delta T_J(t) = K_p(s)\Delta q(t-\tau) + K_v(s)\Delta \dot{q}(t-\tau) \tag{2.2}$$

Where $\Delta T_J(t)$ is the deviation of joint moment from the unperturbed trajectory, $K_p(s)$ and $K_v(s)$ are the position and velocity feedback gains, Δq and $\Delta \dot{q}$ are the deviation joint angles and velocity from the unperturbed reference trajectory respectively and τ is the neural delay, which was initially set to 80 ms for every joint to model the shorter latency of the local reflexes. By following the categorization of lower limb powered orthosis controllers proposed by Baud et al., we can classify this model as a function of joints instant states (FJI) based controller [78].

2.2.3 Linear regression

With the intention of reproducing the closest torque as possible to reality with both presented models, the feedback gains K_p and K_v had to be tuned to match the experimental data. Additionally, optimal gains, independent of the direction, amplitude or nature of the perturbation, an even on the subject, would be even more optimal.

Hence, we did two least square regressions for each speed: one on each subject individually for every direction and amplitude merged together, and one on pooled inputs and outputs for all subjects and perturbations combined. To achieve the linear regression, we used *mldivide* Matlab integrated function.

Feedback gains being phase and speed dependent, we evaluated the linear regression at a discrete time instance, when COM kinematics seem to have the largest deviations form the unperturbed situation. The discrete time instances were at 150 $[ms]$ after the onset of the perturbation in addition to the neural delay for the output. A visual representation is given in Figure 2.2.

2.2.4 Statistical analysis

With the aim of assessing the quality of different model fits, we will use three different statistical tools: the uncentered determination coefficient (R^2), also called R-squared,the root mean square error (RMSE) and the p-value of a paired t-test.

First, the uncentered determination coefficient gives a measure of how the variation in one variable can be explained by the variation in another variable. In the context of comparison between different models, it provides a measure, between 0 and 1, of the goodness of reconstruction of experimental data by a model [98]. In other words, how well the model reconstructs the observed data. The mathematical expression of R-squared is given by equation 2.3, where $y_{i,data}$ is the measured joint moment from the experimental data base at time i, $y_{i,mod}$ is the reconstructed joint moment by the different models at time i and n is the number of time steps.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{i,data} - y_{i,mod})^2}{\sum_{i=1}^{n} y_{i,data}^2} \tag{2.3}$$

For our purpose, we will use this statistical tool to assess our linear regression quality. Moreover, this measure is the square of the correlation coefficient (R).

The second tool that we are going to use, is the root mean squared error. Widely used

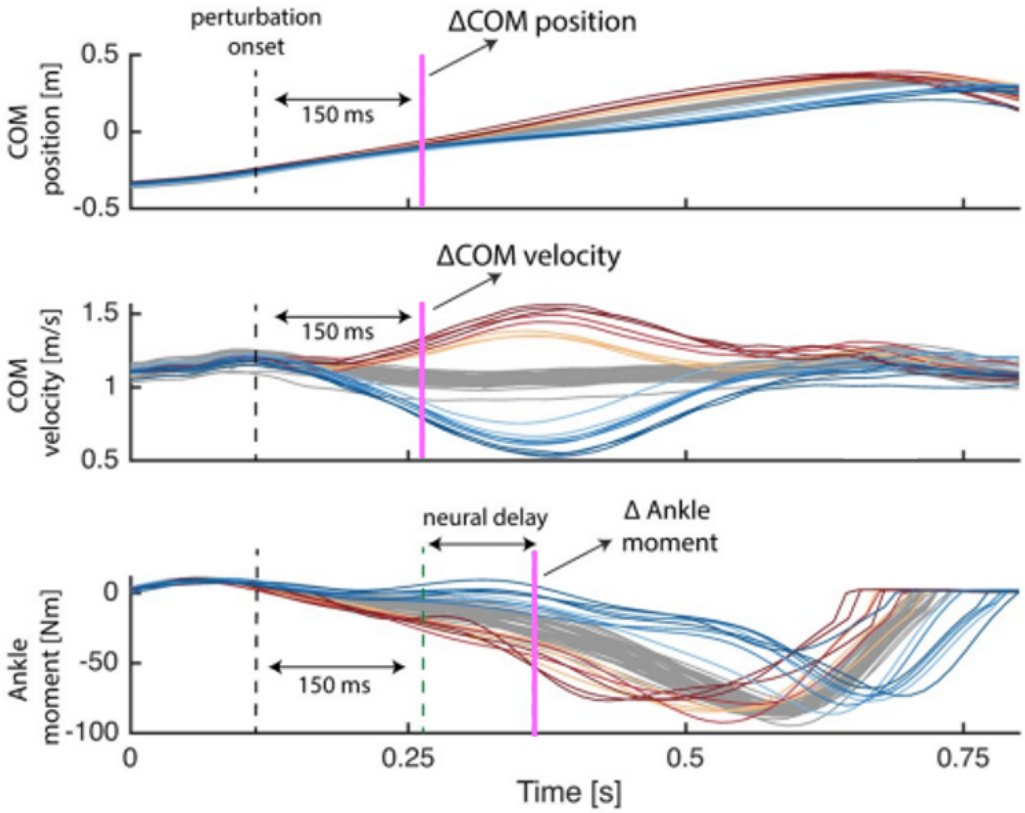


Figure 2.2: Overview of the discrete assessment time (pink line) of the least-squared regression for the ankle joint in the COM feedback model [82].

to assess regressions, it gives the standard deviation, the amount of dispersion, of the residuals (the errors), which are the difference between the experimental data and the regression values [99]. Its mathematical expression is given in equation 2.4, where $y_{i,data}$ is the measured joint moment from the experimental data base at time i, $y_{i,mod}$ is the reconstructed joint moment by the different models at time i and n is the number of time steps.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_{i,data} - y_{i,mod})^2}{n}} \tag{2.4}$$

For our purpose, we will also use this statistical tool to assess our linear regression quality for each model and speed of walking.

The last statistical feature, is the p-value of a paired t-test that we are going to use as a comparative tool, to assess the significance of the differences between the two discussed models results. This measure is going to allow us to determine if the the difference between both models is significant enough to conclude a task-level or joint level control of the joints. One the one hand, the paired t-test is going to compare the means of R^2 and RMSE for each model and test if they differ (null hypothesis: means are equal). On the other hand, the p-value is going to give us the statistical significance of this test, with an arbitrary chosen significance level of $\alpha = 0.05$ [100].

2.2.5 Sensitivity of the neural delay

In compliance with the articles [95] [101], if the joints' response to a perturbation can be explained by task-level feedback, the muscles responsible for the generation of their torque have long-latency electromyographic (EMG) responses reflected by a neural delay between 70 to 100 $[ms]$ for lower limbs. Leading to slightly larger neural delay values for joint due to additional delay related to the force generation in the muscles. For local-joint level feedback, the neural delay should be shorter than the ones of the task-level feedback as they are not centrally-mediated neuromuscular responses.

Therefore, we began our study by mimicking Afschrift *et al.* methodology and computed the linear regression with a time delay of τ = 100 $[ms]$ for the three joints (value taken from literature). Afterwards, we analyzed the sensitivity of the delayed COM feedback model towards the neural delay in order to check the plausibility of the chosen value of 100 $[ms]$.

For the ankle, we reproduced the sensitivity analysis of the article and obtained similar graphs, presented in Figure 2.3. For the lower speed, at the left side of the chart, a time delay of 100 $[ms]$ seemed a justified choice, as the maximum R^2 of the pooled curves is equal to the chosen value. For the higher speed, the maximum of the pooled curved is lower than 100 $[ms]$, but the behavior of the graph is pretty flat around it, with similar R^2 values. Moreover, physiologically a neuronal delay should not change based on the walking speed. Consequently, a value of $\tau_A = 100\ [ms]$ is completely plausible. Therefore, we decided to keep that value for the ankle joint moment reconstruction for the COM model. Moreover, the value of $\tau_A = 80\ [ms]$ for the joint model is also kept as it still models the lower latency period compared to the COM delay.

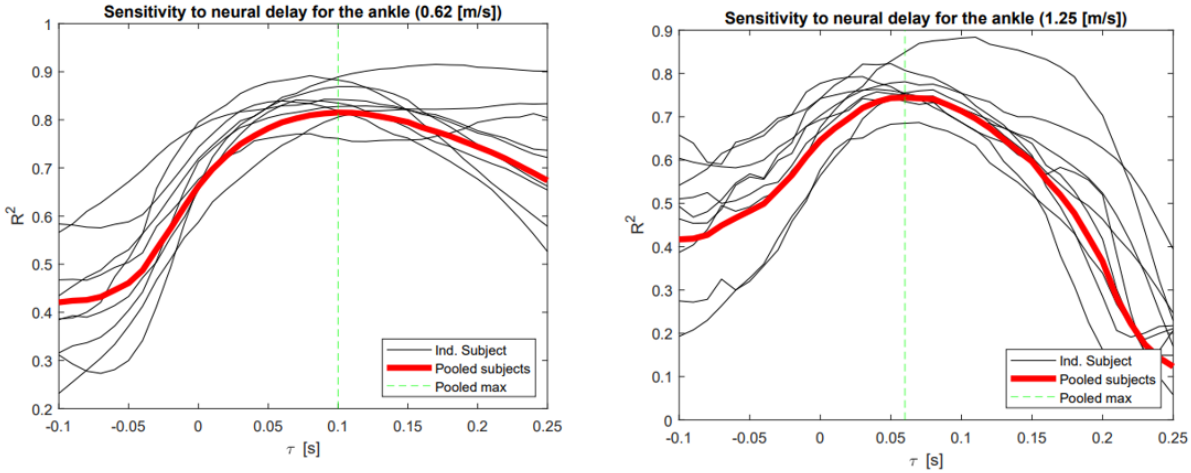


Figure 2.3: Sensitivity of the COM feedback model to the neural delay for the ankle for both speeds, where the green dotted line represents the maximum of the pooled data (red) and the black lines are the data for each subjects.

The first addition to the article is the COM sensitivity analysis to time delay for the knee. A first major difference compared to the ankle, that we can see in Figure [?], is that the different maxima of the pooled curves seem lower for both speeds. Indeed, for the lower velocity we can still observe a flattening zone of around 80 $[ms]$ and not 100 $[ms]$. For

the 1.25 m/s speed, the curves seem more dispersed and less gathered than in the other cases. Based on these Figures, we can assume that taking a lower neural delay, would lead to a better quality of reconstruction of our signal. Furthermore, physiologically it is a meaningful insight, as the location of the knee being above the ankle it would be rational to conclude that it would thus lead to a quicker reception of the nervous commands. Therefore, to enhance our model quality and to be in accordance with physiological phenomenons, we decided to take a neural delay lower than 100 $[ms]$ but still higher than the one produced by the local joint model, as we hypothesized long latency EMG responses from the surrounding reactive muscles of the knee to a disturbance. For the following sections, the neural delay for the knee joint will be of $\tau_K = 80\ [ms]$ for the COM model and of $\tau_K = 60\ [ms]$ for the joints model.

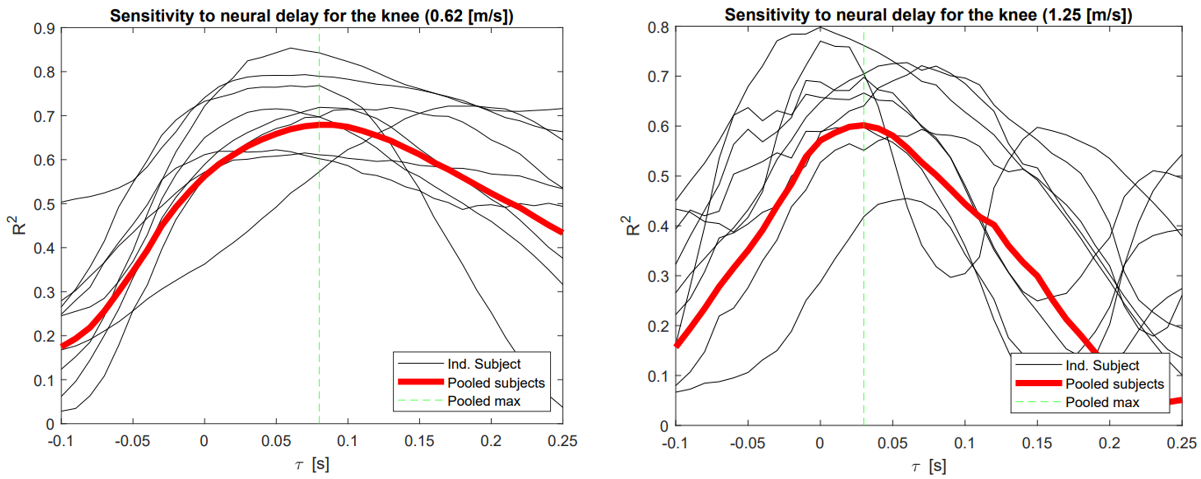


Figure 2.4: Sensitivity of the COM feedback model for the knee for both speeds, where the green dotted line represents the maximum of the pooled data (red) and the black lines is the data for each subjects.

Finally, as the ability of the COM feedback model to explain the hip reactive moments response to a pelvic perturbation was not efficient (cf. section 2.3) a sensitivity analysis seemed unnecessary. For informative purposes, we presented the obtained sensitivity graphs in Appendix D.1.

2.3 Results

In this section, we will evaluate the ability of the different models to assess the lower limb joint reactive moments using the statistical tools presented previously. The results discussed in this section will be used for the data-driven approach of Chapter 3.

2.3.1 Tracking inputs

Before presenting the results of our linear regression, we wanted to present the moment inputs that our different models are aiming to track, to show how a disturbance leads to moments deviation. Afschrift *et al.*, showed that the adjustment of the ankle joint moments, in response to a perturbation, was the result of a reactive balance control

response.

One of the main objectives of this chapter, is to test the ability of the delayed feedback models to reconstruct the moment deviations, that we can see in Figure 2.5. Graphically, we can observe that the largest deviations from the unperturbed trajectory occur between 0.2 and 0.4 seconds after the end of the perturbation, for the three joints, and seem to restore the unperturbed torques behavior just after.

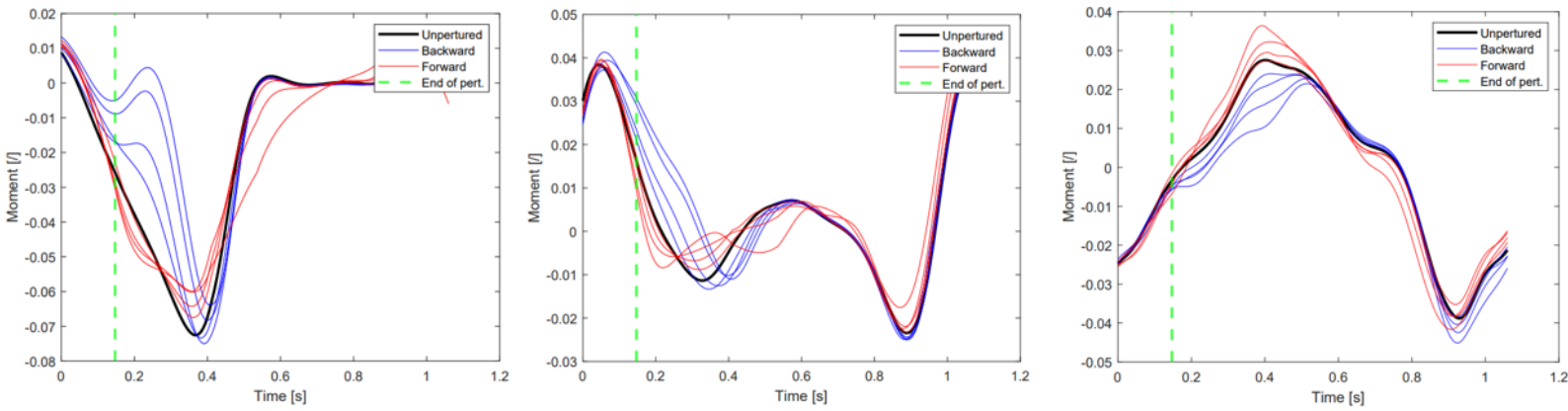


Figure 2.5: Deviation of lower limb joints moments during backward (blue) and forward (red) perturbation of different amplitudes from their unperturbed value (black) - Ankle (left), knee (middle) and hip (right) for a walking speed of 1.25 $[m/s]$.

In this Figure, we can see a representation of the left stances leg joints, where the perturbation has been applied at right leg toe-off (at time 0 in the Figure) during 150 $[ms]$. The torques and COM inputs of the model have been normalized[1] by dimensionless subject physical features. Indeed, the scaling objective was to ease the comparison between the subjects and to allow the computation of common feedback gains over pooled data.

2.3.2 Model fit

As explained in the methodology section, the quality of the fit of the two models, is going to be assessed by different statistical tools. As a reminder, we set the significance level of the p-values at $\alpha = 0.05$. The different results are summarized for both models and speeds in Table 2.1 and Table 2.2.

The first goal of this chapter was to reproduce the results of Afschrift *et al.* for the ankle moments. On the one hand, we had to show the ability of the delayed COM feedback model to model the deviations of the ankle moments. On the other hand, we wanted to show that this adjustment were the result of a task level control for the reactive balance and not a deviation arising from a local reflex control. By looking at the R^2 and RMSE values for the ankle moment for both speeds, we obtain similar values compared to the ones in the article. We can see that compared to the joint feedback model, the COM feedback model strongly reconstructs the ankle moments, with values of R^2 above 70%.

[1] COM positions were scaled by l_{max}, speeds by $\sqrt{gl_{max}}$ and torques by mgl_{max} where l_{max} is the COM height during quiet standing (lmax), m the body mass of the subject and g the gravitational acceleration

Table 2.1: Summary of RMSE and R^2 values of the linear regressions between the delayed models and the reactive joint moments in perturbed walking for a walking velocity of 0.62 $[m/s]$. Joint moments are reported pooled over all subjects (Pooled) and for individual subjects (Subj.).

Speed: 0.62 [m/s]	COM feedback model		Joint feedback model		P-values	
	R^2	RMSE	R^2	RMSE	p - R^2	p - RMSE
Ankle moment (pooled)	0.83	0.02	0.02	0.04		
Ankle moment (subj.)	0.84	0.02	0.2	0.04	< 0.01	< 0.01
Knee moment (pooled)	0.61	0.01	0.47	0.01		
Knee moment (subj.)	0.66	0.01	0.54	0.01	0.17	0.07
Hip moment (pooled)	0.25	0.01	0.55	0.01		
Hip moment (subj.)	0.33	0.01	0.54	0.01	< 0.01	0.05

Table 2.2: Summary of RMSE and R^2 values of the linear regressions between the delayed models and the reactive joint moments in perturbed walking for a walking velocity of 1.25 $[m/s]$. Joint moments are reported pooled over all subjects (Pooled) and for individual subjects (Subj.).

Speed: 1.25 [m/s]	COM feedback model		Joint feedback model		P-values	
	R^2	RMSE	R^2	RMSE	p - R^2	p - RMSE
Ankle moment (pooled)	0.75	0.02	0.2	0.03		
Ankle moment (subj.)	0.76	0.02	0.3	0.02	< 0.01	< 0.01
Knee moment (pooled)	0.6	0.01	0.5	0.01		
Knee moment (subj.)	0.61	0.01	0.54	0.01	0.16	0.05
Hip moment (pooled)	0.35	0.01	0.37	0.01		
Hip moment (subj.)	0.38	0.01	0.40	0.01	0.55	0.2

Furthermore, the rounded RMSE values, seem equal or higher for the joint model. The difference of goodness of the fit between the different models to reconstruct the ankle moment are statistically significant, as the different p-values are lower than the chosen significant level $\alpha = 0.05$. Therefore, these results confirm, that there is a modulation of the ankle moment in response to a perturbation of the pelvis and that this can be modeled efficiently by a COM feedback model.

One of the additional discussions that we bring to the article, is the adaptation of the analysis, to the knee. We can see that the ability of the COM model to reconstruct the

knee moments for the pooled and for the individual subjects is lower than the one from the ankle. Nevertheless, we obtain R^2 values superior to 60% for both speeds for the COM models and values around 50% for the local joint model. However, the difference between the efficiency of the two studied models is not significant with p-values superior to α, except for the p-RMSE of the quicker walk. Indeed, we can see that RMSE values seem pretty similar in every studied situation. This means that we cannot conclude a task level control of the knee moments, even-though the R^2 are still slightly higher for the center of mass model. In the next section 2.4, we will try explaining what are the reasons behind the closeness of the responses between the different models, each underlying a different neuromuscular behavior.

The second additional joint that we assessed was the hip. In the Table 2.1 and 2.2, we can see that the modeled moments do not exceed the value of 55% for the uncentered determination coefficient. Consequently, these models do not seem the most appropriates to model the response of the hip moments to a pelvic perturbation. Even though, there seems to be significant difference between both models for the lower speed of walking. However, the close results obtained for the quicker speed could arise from the same causes than the ones for the knee, this will be investigated in the following section 2.4.

A linear regression equation represents the correlation strength between the different variables. The higher the correlation between two variables, the stronger will be the linear relationship between them [102]. For that reason, to better evaluate our models efficiency, we computed scatter plots (representation of correlation strength) to better visualize how the tested model fits the experimental data (represented by a least-square line). The different scatter plots are presented in Figure 2.6 for the ankle and in Appendix E.1 and E.2, for the knee and the hip respectively. Indeed, the difference between both models is most pronounced for the ankle and therefore, seemed to be the most appropriate to present. We can see in Figure 2.6, that the data points follow nicely the least square line for the COM model (left) unlike the local joint model (right).

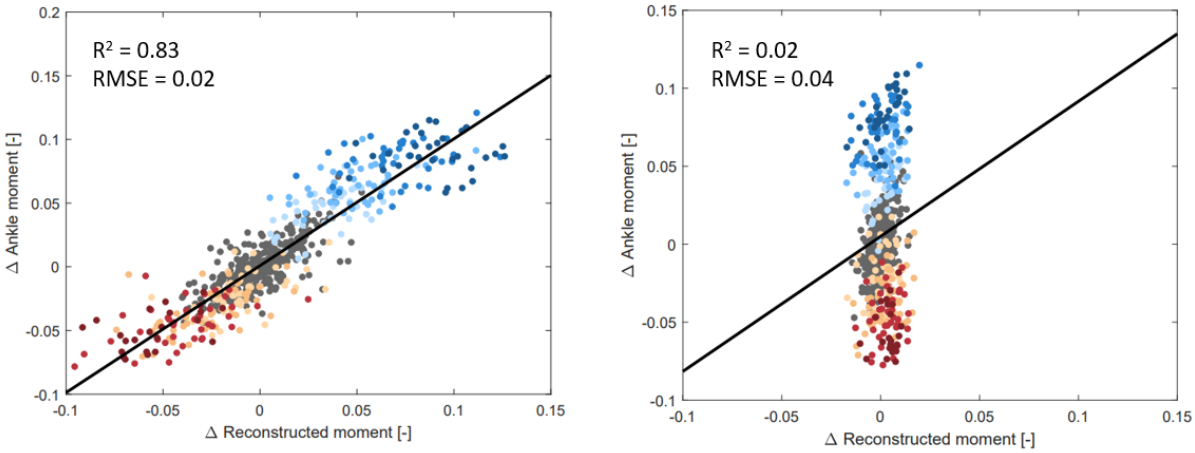


Figure 2.6: Ankle moments (pooled) as a function of the reconstructed moments by COM model (left) and by the local joint model (right) - representation of unperturbed walking (gray dots), forward perturbation (red dots) and backward perturbation (blue dots), speed = 0.62 m/s.

2.3.3 Gains

The last important results to evaluate are the gains, presented in Table 2.3 and 2.4, where K_p and K_v stand for feedback gains relative to the inputs positions and velocities respectively. Indeed, one of our goals was to see if a global gain, independent of the subject, perturbation magnitude or direction, could give a fit as satisfactory, as a subject and perturbation dependent gain.

For the three joints moments, we have seen in Table 2.1 and 2.2, that the quality of reconstruction given by each models does not vary much from the pooled or individual situation. This is an encouraging finding in regard to the expectation of common feedback gains. To support this statement, we can see that the gain values in themselves do not vary much either, with a maximal deviation of 0.4, in Table 2.1 and 2.2.

Table 2.3: Summary of the different feedback gains for the delayed models for a walking velocity of 0.62 $[m/s]$. Joint moments are reported pooled over all subjects (Pooled) and for individual subjects (Subj.).

Speed: 0.62 [m/s]	COM feedback model		Joint feedback model	
	K_p	K_v	K_p	K_v
Ankle gains (pooled)	-0.79	-1.03	-0.18	-0.01
Ankle gains (subj.)	-0.82	-1.06	-0.28	-0.01
Knee gains (pooled)	-0.35	-0.43	-0.22	-0.02
Knee gains (subj.)	-0.33	-0.47	-0.21	-0.02
Hip gains (pooled)	0.04	0.17	-0.07	-0.01
Hip gains (subj.)	0.04	0.17	-0.07	-0.01

Table 2.4: Summary of the different feedback gains for the delayed models for a walking velocity of 1.25 $[m/s]$. Joint moments are reported pooled over all subjects (Pooled) and for individual subjects (Subj.).

Speed: 1.25 [m/s]	COM feedback model		Joint feedback model	
	K_p	K_v	K_p	K_v
Ankle gains (pooled)	-1.07	-0.61	-0.61	-0.004
Ankle gains (subj.)	-1.07	-0.63	-0.65	-0.0008
Knee gains (pooled)	-0.54	-0.20	-0.19	-0.03
Knee gains (subj.)	-0.56	-0.2	-0.2	-0.03
Hip gains (pooled)	-0.02	0.17	-0.03	-0.01
Hip gains (subj.)	-0.04	0.18	-0.02	-0.01

2.4 Discussion

In Chapter 1, we have seen that the ankle strategy was a reactive corrective balance strategy, involving deviations of the ankle, knee, and hip flexor/extensor moments. Afschrift *et al.*, showed that the modulation of the ankle torque, underlay a task level control feedback and not a local joint level one. We followed the same methodology in order to check whether the knee and the hip joint responses to a pelvic perturbation were also reflected by a task level delayed sensory motor feedback. In the findings presented previously, we saw that the results were different from one joint to another. The variability of the results for the different joints could be explained by divergent feedback mechanisms. In this section, we tried finding explanations about the differences for each reconstructed joint behavior within the different models and between the different joints.

2.4.1 Intra-model behavior

This part of the discussion aims at understanding the reasons for similar results between both models while the inputs are completely different. Indeed, we observed in Table 2.1 and 2.2, that particularly for the knee, the goodness of the fits between the COM and the joint feedback model were pretty similar. A pathway to explain this, could be the fact that both inputs, the joints and COM kinematics, are highly correlated, leading therefore to similar results. To do so, we used the linear correlation coefficient, R, which provides a quantification of the degree to which two variables vary together. Moreover, we plotted a scatter plot to have a visual support. We tested the knee moments at low speed and the hip moments at high speed, which were the two situations where the differences between models statistics, where not significant (cf. non-blue p-value squares in Table 2.1 and 2.2). The different results are presented in Figure 2.7.
Visually we can already see that the data points are widely spread around the least-square line, involving a low correlation. Secondly, by looking at the R values (top left in Figure 2.7), it confirms the low correlation between the inputs, with only 1 of the situations going beyond 50%. Therefore, we cannot conclude that a correlation between the inputs could be at the origin of similar results between COM and joint models.

2.4.2 Sensorimotor transformation underlying reactive balance

Balance in humans demands a feedback control of the central nervous system which will activate the necessary motor responses by integrating information from sensory inputs [103]. However, this transformation of sensory inputs into motor commands is not well understood yet for the control of balance during walking. The idea of Afschrift et al. was to test whether the sensorimotor transformation control during perturbed standing could be applied to walking some time after the perturbation onset (long latency). Indeed, several authors showed that muscular activation, in order to control balance of perturbed standing, was done through an estimation of the center of mass movements. By showing the proportionality between COM kinematics and the ankle joint moment adjustment, they showed that similar sensorimotor transformation processes underlaid ankle reactive moment adjustments during ankle strategy. This implies a feedback control driven by the COM kinematics, to generate the appropriate behavior for reactive balance. Through the integration of sensory input, the central nervous system estimates COM movements

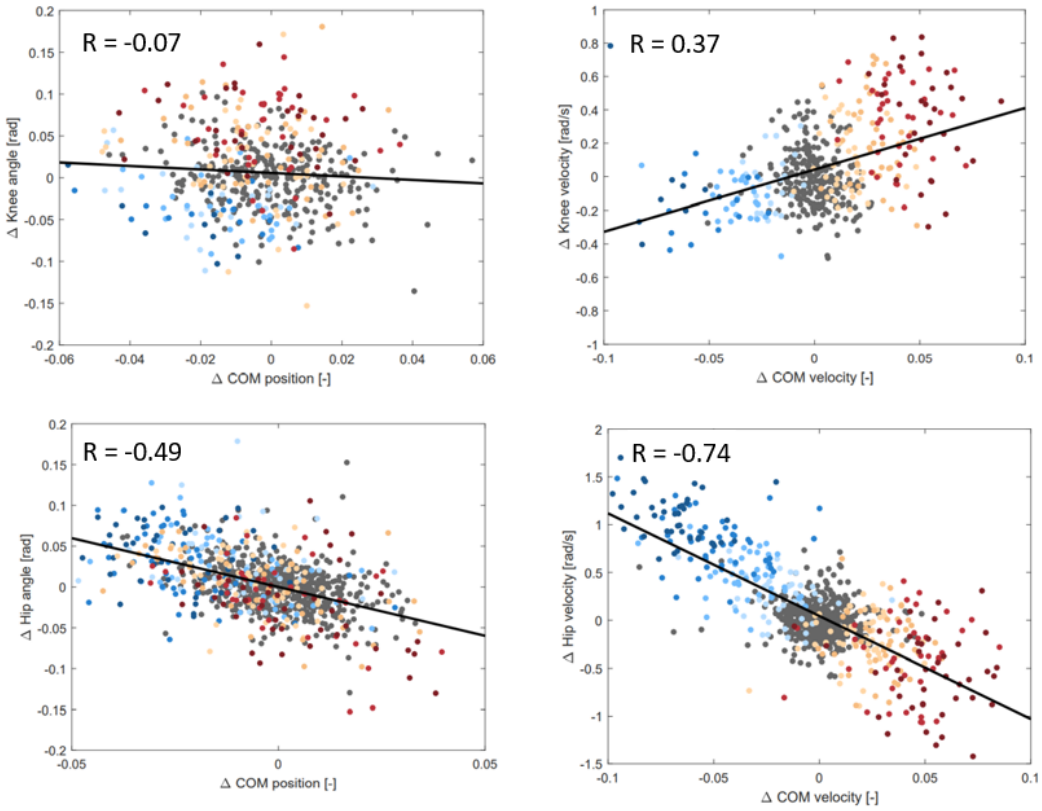


Figure 2.7: Scatter plots of the inputs of local joint model as function of COM model inputs. Top Figures - For the stance knee joint at low speed (0.62 $[m/s]$). Bottom Figures - For the stance hip joint at high speed (1.25 $[m/s]$).

leading to the appropriate motor command actions. This kind of sensorimotor transformation are called task-level feedback, where the center-of-mass kinetics are the task-level variables[2]. Different studies suggest that spinal central pattern generators (CPG) are responsible for task-dependent modulation of sensory feedback during locomotion [104].

Our different results regarding the relation between the knee and hip torques with COM kinematics during the ankle strategy, suggest a different sensorimotor transformation. Indeed, a different neuromechanical control for proximal and distal joints in response to a perturbation could explain the variances in the results. For instance, Daley *et al.*, showed that a proximo-distal gradient neuromechanical control could explain the improved stability during running [105]. Furthermore, Nataraj et al., showed that a feedback control, merging local joint variables and center of mass kinematics, supplied more stability against standing perturbation than controller based only on local or task-level feedback [106].

The similar results between the COM and the local joint models for the hip and knee joints, could be explained by the fact that the resulting reactive moments stem from both delayed local (joint-level feedback) and long latency reflexes (task-level feedback).

[2]Task-level variables can be defined as "motor variables that cannot be directly encoded or controlled by any unique sensory input or motor output" [95]

This would explain the similar intra-model behavior and moreover, it could also describe why the COM feedback model cannot achieve as efficient results as for the ankle joints. This would mean that the torques deviations of the knee and the hip could be the combination of direct stretch reflexes to come back to the unperturbed posture and of functional reactive balance adjustment. A reason behind these different neuromuscular behaviors between joints, could be given by the delayed muscular activation rising in a distal-to-proximal fashion for lower limb muscles during the ankle strategy. Indeed, some authors have shown that due to this delay, the stretch reflexes in the knee and in the hip occurred 20 to 70 $[ms]$ after the ankle local reflexes responses [48]. Moreover, depending on the assessed discrete time, lower limb moment adjustment origins, following a sagittal perturbation, can be divided in three categories according to Ferber and his team:

1. Just after the onset of the perturbation (< 70 ms): Moment deviations come from mechanical responses due to viscoelastic changes of the surrounding tissues in response to the disturbance.

2. 70 to 250 ms after the onset: Joints' responses arise from mechanical and local stretch reflexes.

3. Over 250 ms after the onset: The joints' adjustments are a combination of mechanical, local reflex and cortically-mediated neuromuscular responses.

2.5 Conclusion

The objectives of this chapter were two folded: first, to find a bio-inspired model appropriate for a mid-level orthosis controller reactive balance assistance. Through the assessments of the obtained data, we validated the fact that the delayed COM feedback model was an appropriate model to describe and explain ankle reactive behavior in response to a perturbation, at 250 $[ms]$ after the onset of the perturbation. Unlike the knee and the hip, where none of the tested model were adequate to explain these lower limb joints moments behavior at the same discrete time. Second, both models had been chosen to show if they could bring us more insights about the sensorimotor transformation underlying the reactive balance. Thanks to the comparison of the results of both models, we found that the ankle and distal joints were driven by different sensorimotor transformation at the assessed discrete time. We proposed a possible path of explanation with the delayed distal to proximal muscular activation approach of the ankle strategy.

Therefore, by validating Afscrift *et al.* conclusions, we showed that the COM feedback model could be a potential reactive balance controller for ankle active orthoses. Indeed, by predicting the supposed reactive balance moments that a healthy subject should have in response to a certain perturbation, the reduced reactive balance abilities of the wearer could be compensated by torques generated through the orthosis thanks to this relationship. A deeper understanding of the sensorimotor transformations underlying knee and hips joints during perturbed walking, could led to future efficient models for the three joints.

Limitations

A first limitation of this thesis lies in the methodology of this chapter. Indeed, we only tested our models on one experimental data set which was already used by our pioneer article. For a proper validation, a different data set should have been used.

Chapter 3

Adaptation of a neuromuscular bipedal locomotion model

In this chapter, we attempt at assessing a model-based controller via its implementation in a 2D neuromuscular locomotion model.

3.1 Introduction

In the previous chapter, we described the ability of a center-of-mass kinematic based model, to explain reactive balance of lower limb joints in response to a perturbation, established on experimental data. The following step is to identify if it can supplement a pathological balance behavior in order to get closer to a healthy balance control conduct. Unfortunately, it is not trivial to find experimental data with the targeted pathological features following similar test protocols.

Nevertheless, a solution lies in using computational models. More and more, there is an increasing use of in silico models to predict in vivo outcomes [107]. Indeed, according to Mallet, D. G.: *"In silico experimental modeling (...) involves combining findings from biological literature with computer-based models of biological systems in order to conduct investigations of hypotheses entirely in the computer laboratory"* [108]. Therefore, we could use a computational model mimicking human locomotion, based on biological facts, inhibit its reactive balance control system and test our model-based controller on it, to predict its effectiveness on pathological balance subjects. Therefore, we looked for in silico models adapted to our study and found a promising reflex-based neuromuscular model of human locomotion proposed by Professor and researcher Hartmut Geyer [109]. A big advantage of this model, is that the 2010 version, is free and available online for academical research. In addition to that, it has been shown that this version, is not able to provide a satisfactory human-like behavior of joint moments in response to an anterior or posterior perturbation. Providing us a direct platform to test our reactive balance controller on a reduced balance computational model [88][89][110].

3.2 Geyer's Neuromuscular Locomotion model

The main principle that Geyer's neuromuscular model tries to simplify, is the control of an intricate nervous network behind the legged locomotion in humans. In scientific literature, it has been shown that the core of this complex network is a mix between the locomotor central pattern generator (CPG) and the spinal reflexes [111]. Indeed, a locomotor CPG is a gathering of different neurons centralised in the spinal cord of every mammalian, with the responsibility to generate rhythmic outputs with no input of rhythmic information from either the higher nervous levels or from peripheral sensory feedback [112]. Besides the CPG, there are the spinal reflexes, which are going to supplement the CPG by providing the timing of muscular activities, the choice of the motion pattern and the adjustment of the CPG output [113][111]. The presented neuromuscular model aims at simplifying this complex structure underlying legged mechanics to elucidate its influence on human motor control.

3.2.1 Description

In the 2010 version, the presented neuromuscular model integrates leg mechanics in autonomous muscular reflexes. First of all, to make the model as human like as possible they created a 2D segmented rigid body representation with shanks, thighs and feet for each leg and a common trunk, as we can see in the middle of Figure 3.1 (the black segments). Moreover, we can observe that each of this body parts are linked by the ankle, the knee and the hip joints (white circles in Figure 3.1).

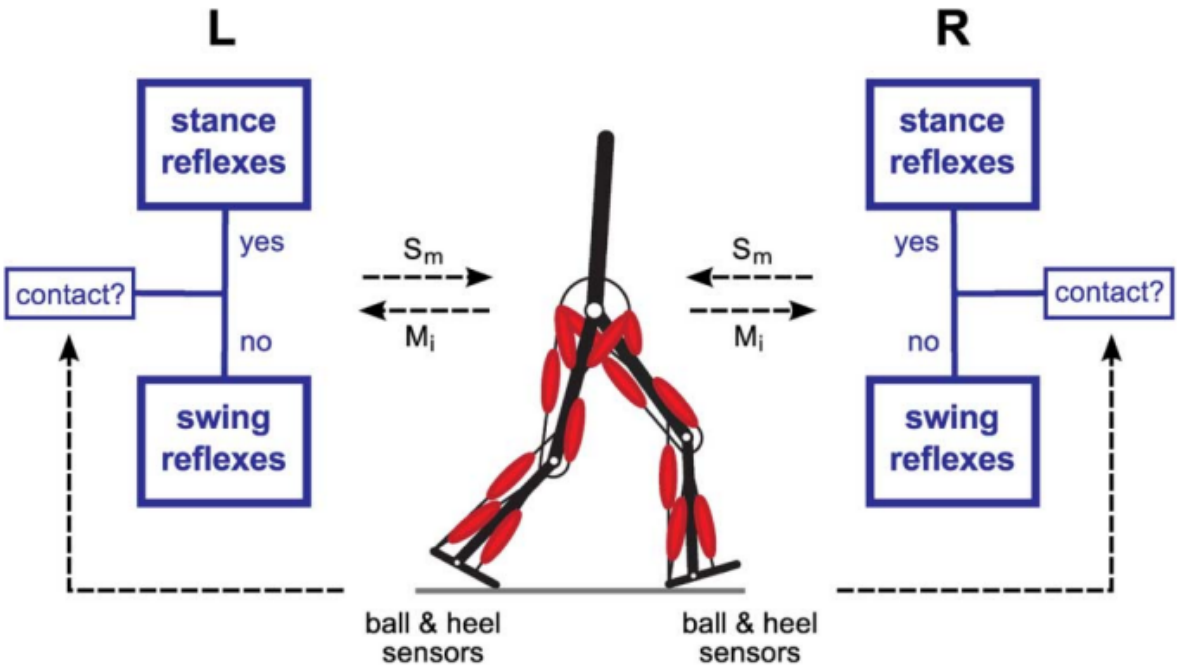


Figure 3.1: Feedback motor control representation of the neuromuscular model [111].

In order to induce locomotion, each joint is actuated and constraint by seven Hill-type muscles (cf. section 1.4.2): the soleus, the tibialis anterior and the gastrocnemius for the ankle, the vastus and the hamstrings for the knee and the hip flexors and the gluteus for

the hip joint. The model underlying this segmented body is divided in two main control systems: the left and the right, each responsible for the left or right leg respectively. Moreover, these systems are in turn divided in two reflex-control systems dependent on the gait phase (swing and stance) which are detected thanks to virtual ground sensors. Geyer's proposed an efficient simplified locomotion model driven by muscular reflexes and with no central pattern generator.

3.2.2 Layers of the model

In order to achieve bipedal locomotion of such a model, Geyer *et al.*, divided the system in three main layers: the neural, the muscular and the mechanic layers. These levels interact among each other via different relationships presented in this section in order to reach a model that can walk on different slopes, ground levels and surfaces. For more information, the details are broadly explained in article [111].

3.2.2.1 Neural control layer

The neural control layer is responsible for the generation of the reflexes underlying the model. This control is based on three concepts, through which human-like leg mechanics during walking, has been implemented. The three concepts are:

1. Generation of compliant stance behavior by the ankle and knee extensors muscles via positive force reflexes generating muscle activity. The stimulation of the muscles has been modeled with the following equation:

$$S_m(t) = S_{0,m} + G_m F_m(t - \Delta t_m)$$

   Where $S_m(t)$ is the stimulation of the muscle 'm', $S_{0,m}$ is the pre-stimulation of muscle 'm', F_m is the reflex forces, G_m is the different gains and Δt_m the neural delay.

2. Balance control of the trunk via the stimulation of the gluteus and the hip flexors by a proportional derivative signal.

3. Swing leg control to enhance cyclic motion.

These three concepts enable the model to generate a cyclic locomotion while having a compliant leg behavior in stance and proactive balance control of the trunk. The authors did not represent the CPG which normally actuates the muscles feed-forwardly. Indeed, in the model, the muscle's stimulations are produced by reflexes which switch from stance to swing reflexes via sensors from the body mechanic's layer.

3.2.2.2 Muscle actuation layer

Thanks to the neural control layer, muscular stimulation is generated. The muscular actuation layer links this neural stimulation's with the force that the corresponding muscle is going to provide in response. The seven couple of Hill-type muscles follow an adapted architecture of the primary Hill muscle model (cf. Figure 1.3), presented in Figure 3.2. The model is called the muscle-tendon model which represents a muscle tendon unit (MTU). In the center of the model, we find the basic Hill muscle model linking the active

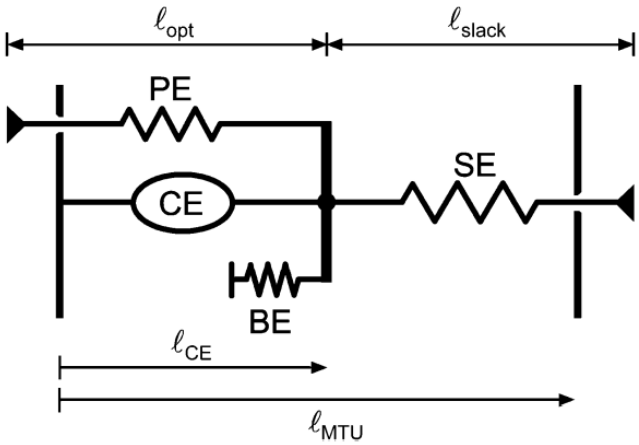


Figure 3.2: Muscle-tendon model where CE is the contractile element, SE a series elasticity, PE a parallel elasticity, BE a buffer elasticity and l_i represent the length of the different subparts of the model [111].

contractile element with the series elasticity, representing the MTU in standard condition. Whenever the contractile or the series elasticity goes beyond or below a certain threshold in length, the parallel and buffer elasticity prevent the collapsing of the CE.

Based on this architecture, the generated force of the MTU can be expressed by equation 3.1, where F_{CE}, F_{PE} and F_{BE} are the forces of the contractile element, the parallel and buffer elasticity respectively. Their sum results in the MTU force, F_m, of muscle 'm'.

$$F_m = F_{CE} + F_{PE} - F_{BE} \tag{3.1}$$

The relation between the neural and the muscular layer is given in the expression of the contractile element: $F_{CE} = AF_{max}f_l(l_{CE})f_v(v_{CE})$, where A is the muscle activation, which is linked by a first order differential, to the stimulation of the neural layer. The other terms of the expression correspond to: F_{max} the maximum isometric force, $f_l(l_{CE})$ and $f_v(v_{CE})$ the force length and force velocity expressions of the CE.

3.2.2.3 Body mechanics layer

The last main layer is the body mechanism system. Herein, the different segments, represented by rigid bodies, are connected between them through the joints. Moreover, we have the transfer of force between the muscle tendon units and the joints. Indeed, the motion of the skeletal system is done through the joint, as we explained in Chapter 1. The transfer of force from the muscular to the body mechanics layer, is expressed by the relation 3.2, where τ_m is the joint torque produced by muscle 'm', F_m is the MTU force, r_m is the lever arm and ϕ the joint angle.

$$\tau_m = r_m(\phi)F_m \tag{3.2}$$

Also, we can find, within this layer, the feet's virtual contact sensors sending the trigger to the stance or swing reflexes to the neural control layer to whether activate stance or swing reflexes. Additionally, another link with this last layer is done through the dependency of the reflex outputs (neural) on mechanical information (mechanics).

3.3 Method

For the methodology of this chapter, we merged various practices from different teams, who had already tested their reactive balance model on this simulation [88][89][110]. The 2010 version of the model was processed and adapted on Simulink (R2021a, Mathworks) and Matlab (R2021a, Mathworks).

3.3.1 Overall strategy

The aim of this chapter is to assess the effectiveness of our model-based controller, via a neuromuscular simulation of bipedal locomotion. Based on the results of Chapter 2, we decided to implement the COM feedback model in a controller, to enhance reactive balance abilities (making them closer to the ones of a healthy person) by providing an additional torque to the ankle joint.

For that purpose, we first had to adapt the reflex-based model to retrieve the desired inputs of the COM model equation (cf eq. 2.1).

The first inputs to retrieve, were the COM kinematics from an unperturbed reference gait. To allow a synchronized retrieval of the data relative to the perturbed kinematics, we decided to run a simultaneous NMM where the simulated human body would be in a steady walking state and would provide the live necessary reference input to the COM model. An overview of this strategy is displayed in Figure 3.3. By launching the two simultaneous NMM, the different simulated movements and contact will be recorded by the virtual sensors. Afterwards, these sensory signals will be sent to the neural control layer, which will generate muscles' stimulation via reflexes. Additionally, COM kinematics will be sent to the mid-level controller from the reference and perturbed bodies. A virtual inertial sensor had to be added to the NMM body mechanism layer to measure these additional sensory inputs. With our additional features, the deviation torque provided by the output of the COM model supplemented the produced hill-type muscles joints' moments which were then supplied at the ankle joint. We recorded the result of such an implementation, in Movie1[1]. The blue and red rigid bodies represent the reference and the perturbed kinematics respectively. The implementation of the perturbation and of the controller block will be presented in the following sections. After the implementation of the necessary inputs, the output of the simulated models had to be analyzed in order to draw our different conclusions.

3.3.2 Perturbation block

With the aim of assessing the reactive balance control added value of our COM model, an unexpected external perturbation had to be applied to the human-like bodies. To obtain a more reliable comparative study base, we mimicked the disturbance from our model fitting study, where anterior-posterior pelvic perturbations of different amplitudes were given at right toe-off during 150 $[ms]$. The implemented perturbation block, in the body mechanism layer, is reported in Appendix F.1.

[1]Movie 1 = https://youtu.be/h1-pqdpPTeA

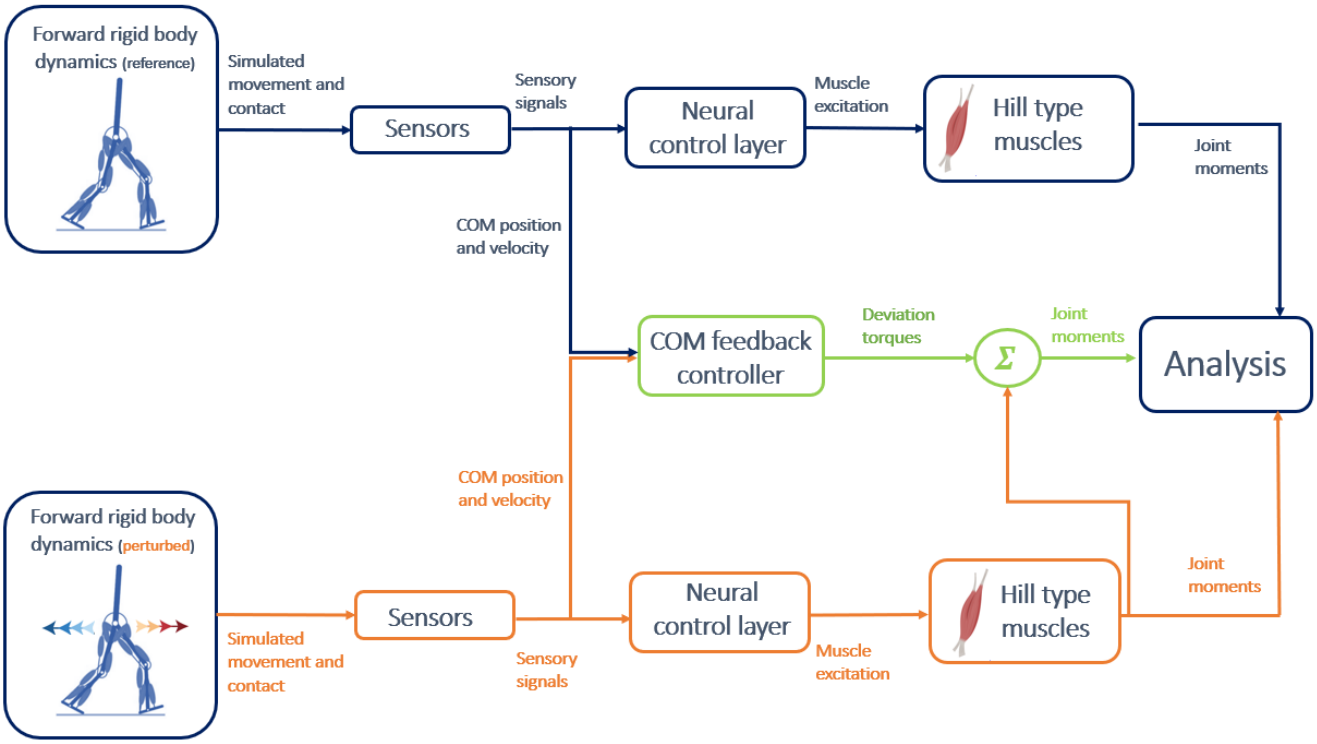


Figure 3.3: Overview of the overall strategy inspired by [88] - the orange path represents the simulated perturbed signals, the blue path represents the reference simulation and the green path the additive torque predicted by the delayed COM feedback model.

To begin with, there is no rigid representation of the pelvis in the neuromuscular model. Nevertheless, the anatomical position of the hip joints are located at each side of the pelvic bone. Therefore, we decided to apply the perturbation at the interface between the hip joints and the trunk segment of the rigid body. We evaluated the reactions of the simulation for different force amplitudes, given by 4, 8, 12 and 16% of the body The mass of the virtual human body, given by m = 80 $[kg]$.

The other challenge in the implementation of this block, was the trigger of the perturbation exactly at right toe-off during 150 $[ms]$. We have seen in the description of the NMM, that the decision to be whether in stance or swing phase, is taken based on the contact sensors of the body mechanism layer. Therefore, we made our block trigger-dependent by connecting it to the decisional pulse of the feet sensors. Furthermore, the toe-off corresponding to the first step of the swing phase, the triggering decisional pulse beginning matched exactly the start of right toe-off. By running the simulation, we observed that the first gait cycles presented abnormal behaviors before reaching a steady human-like walking. For that reason, we applied the perturbation after two seconds of simulation-time not to have biased results.

3.3.3 Controller block

The second important block to implement was the COM based controller block. An overview of the controller is given in Figure 3.4. The first step, is the gathering of the center of mass kinematics. We already stated previously that this has been done through

the use of inertial virtual sensors. These sensors did not provide the velocity of the COM, therefore we had to perform a derivation. Due to the noise brought by the derivative, we applied a filter to provide the cleanest possible signal. Afterwards, these kinematics had to be delayed and multiplied by different feedback gains in order to generate the reactive joint moments. Then they are added to the torques produced by the Hill muscles. Besides the additive action between muscular and predicted moments, the implemented controller block is showed in Appendix F.2.

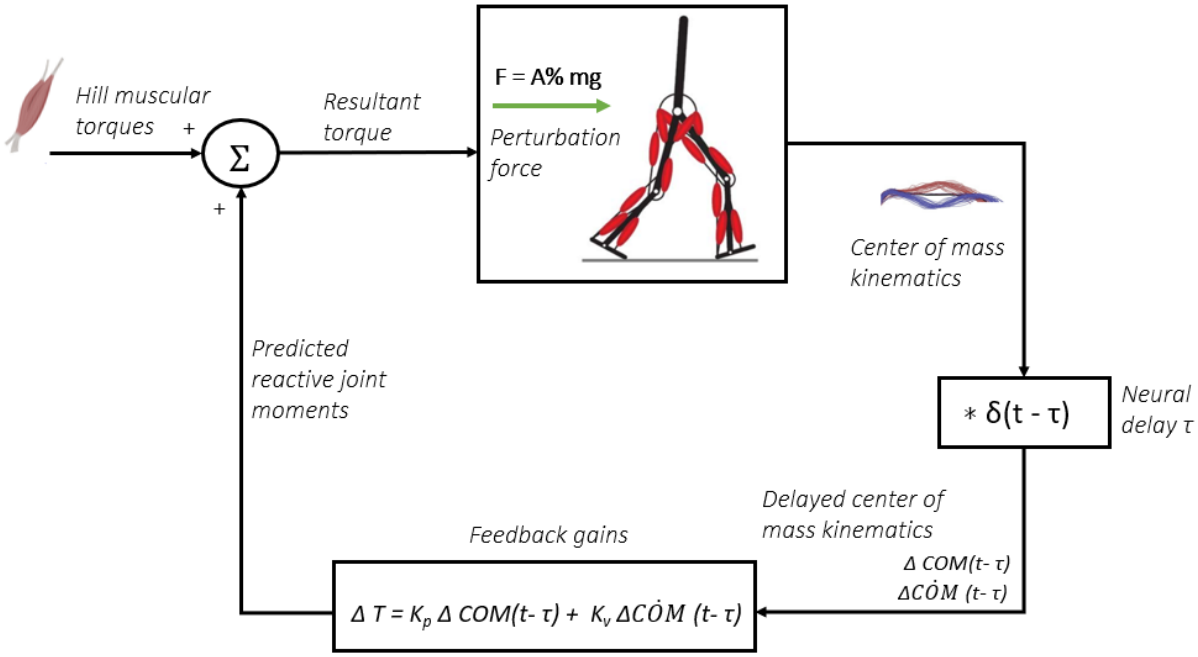


Figure 3.4: Overview of the controller architecture, inspired by [103].

3.3.4 Data-driven approach

Our overall strategy follows a data-driven approach by using inputs from experimental data, to derive our controller which aims at describing reactive joint behavior during the ankle strategy. Indeed, the choice of the studied joint and the different feedback gains have been chosen on the basis of the experimental data set from Chapter 2.

3.3.4.1 Joint moments tracking

With the aim of supporting our joint selection for the COM model-based controller to be simulated, we assessed the ability of Geyer's bipedal model to track the joint moments from Vlutters 2018 data set, during steady walking. Indeed, it is an important feature to test if we want to have a comparative study between the simulated outputs and real results.

Before evaluating the tracking potential of the NMM, we normalized the moments by the product between the COM height during quiet standing (l_{max}) and body weights. For the NMM, we summed up the length of the segment parameters of the shanks and thighs to obtain an approximation of the COM height during quiet standing[2]. Additionally, we

[2]Normalisation parameters : m = 80 [kg], g = 9.81 [ms^{-2}] and l_{max} = 1 [m]

pooled the data over three strides to obtain a representative cycle of the simulation.

Hence, for the appraisal of the joint tracking, we started plotting the different stance leg moment outputs of the unperturbed computational model, to first assess the tracking visually. The results are illustrated in Figure 3.5, where the NMM output is represented in blue and the experimental data in red. The x-axis represents the percentage of gait cycle, starting at right TO.

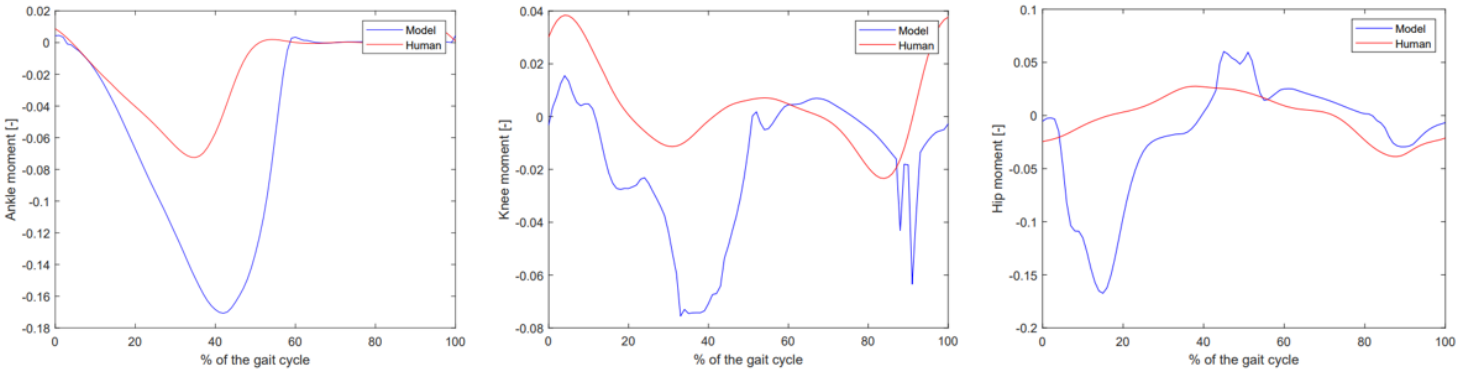


Figure 3.5: Stance leg joint moments as function of the % of the gait cycle given by the simulation (blue) and by the experimental data (red). For each joint, dorsiflexion and flexion movements are conventionally an increase of the moment.

On the left chart, the global behavior of the ankle seems very close to the experimental one but with a high difference of magnitude, particularly around the peak of plantar-flexion ($\pm$ 40% of the gait cycle). In the middle chart, the knee moments simulated trajectory seem to follow less the experimental data with an accentuated extension around 40 %, in comparison with Vlutters data. On the right chart, hip torques seem to follow nicely the experimental data set in the swing phase (after 60 percent) but has an opposite progression for the stance phase with exacerbated extension at the beginning of the cycle. To confirm the reliability of our plots, we compared our results with the ones given by Geyer in his article, where he reaches a cross-correlation coefficient of R = 0.99 for the ankle compared to human data. We confirmed the reliability of our simulated results outputs, as our results are particularly similar to the ones in the article, as we can see in Appendix G.1, G.2 and G.3. Moreover, Keeminck *et al.* implemented a similar controller with the same human data and showed comparable differences between the computational model and the experiments prior to any optimisation [110]. For a proper analysis between our NMM and Vlutters data, a rigorous optimisation of the parameters of the reflex-model would be needed.

Even if the amplitudes are different, some of the simulated moments seem to have a close global behavior to the experimental one. In order to detect this correlation, despite the different amplitudes, we have computed the normalized zero lag cross-correlation indicator, denoted R. Indeed, it gives a measure of the similarity shape of two signals, independently of their amplitude differences. The different results are presented in Table 3.1. If R = 1, the signals are the same but of different amplitudes and if R = 0, they are not correlated at all. In table 3.1, the normalised cross-correlation and RMSE values are

given. As the NMM has distinct reflexes for the stance and swing phase, we divided the analysis in two phases. For our purpose, we needed the best tracking of the stance leg as our COM model aims at reflecting the ankle strategy in this phase.

Table 3.1: Summary of normalised cross-correlation and RMSE values of the difference between Geyer's model and Vlutters experimental data (pooled) joint moments during unperturbed walking for a walking velocity of 1.25 $[m/s]$.

Speed: 1.25 [m/s]	Ankle moment		Knee moment		Hip moment	
	Stance	*Swing*	*Stance*	*Swing*	*Stance*	*Swing*
R	0.85	0.34	0.2	0.44	0.26	0.76
RMSE	0.07	0.005	0.04	0.02	0.06	0.015

These different values show us that the ankle torques are really closely correlated to the experimental data beside its amplitude (with R = 0.85), whereas the knee and the hip show less agreement in stance (R = 0.2 an R = 0.26 respectively). On the contrary, RMSE values seem higher for the ankle than the ones for the knee and the hip. This difference is due to the fact that R gives a measure of the similarities in shape between two signals, whereas RMSE measures how different signals are, dependent on their amplitude. As we are working on pooled data, the significance of these tests differences has not be assessed.

The tracking ability of the computational model, to reflect our used experimental data had the second purpose to support, in addition to chapter 2 conclusions, which joint was going to be assessed throughout the controller in the simulation. Based on the strong cross-correlation for the ankle compared to the other joints and with relatively small RMSE differences within these last ones, we decided to study the ankle reactive control in response to a pelvic perturbation supported by the different conclusions drawn in Chapter 2.

3.3.4.2 Phase-dependent gains

The second important methodological layer where the experimental data is going to step, is directly in the controller block. Indeed, the feedback gains, relative to the position and velocity of the COM, are directly provided by the model fitting of the experimental data, as illustrated in Figure 3.6 via the pink path. In the article studied in Chapter 2, Afschrift and his team, showed a phase and walking speed-dependency of the feedback gains in the delayed COM feedback model[82]. In this respect, we decided to test only one speed of walking, supported by the fact that Geyer's model of 2010 demands a tuning of the parameters to change the velocity of locomotion of the human-like 2D simulation. Indeed, the standard walking speed of the neuromuscular model being 1.3 $[ms^{-1}]$, we

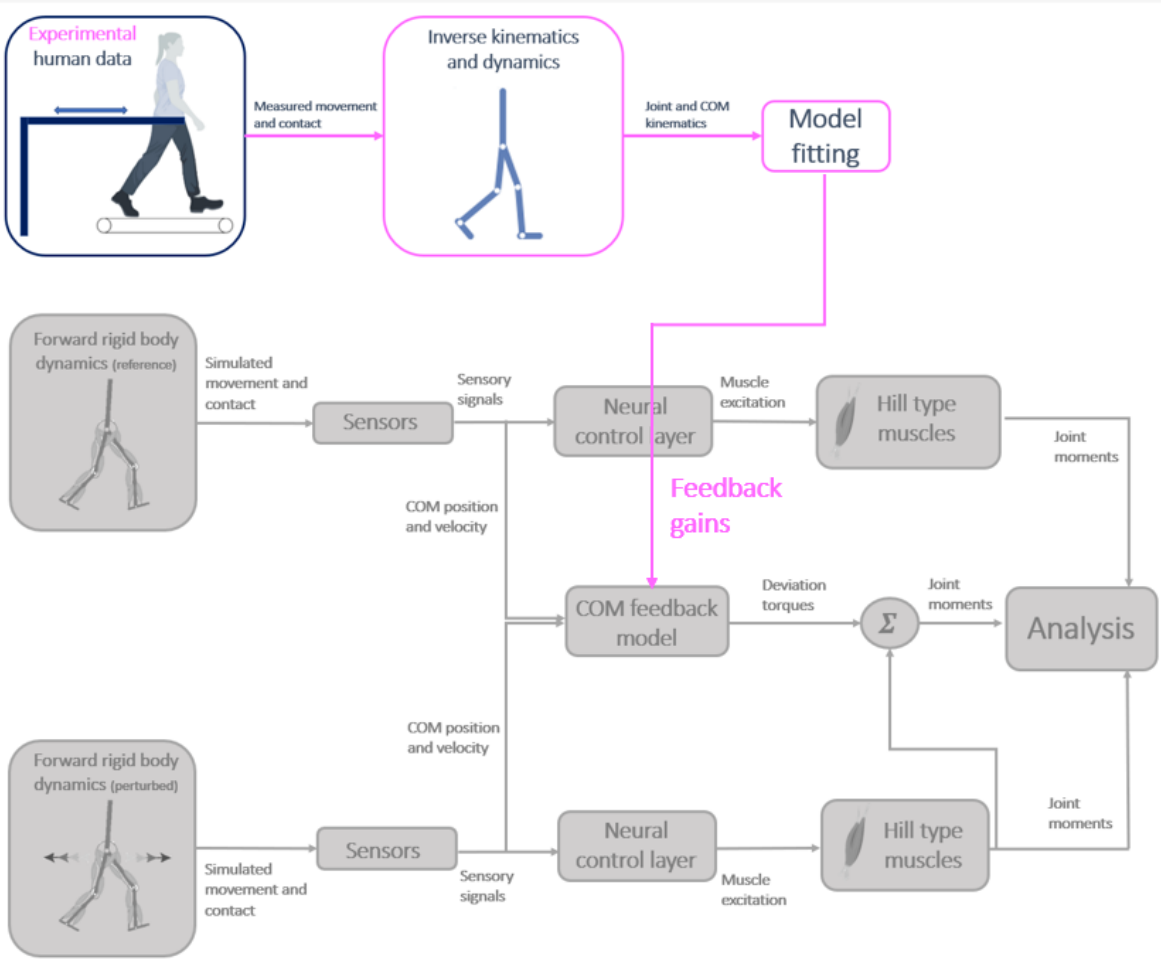


Figure 3.6: Feedback gains integrated via a data-driven approach.

hypothesized that the variances with the experimental data of 1.25 $[ms^{-1}]$ could be neglected.

With regards to the phase-dependency, we followed the conclusions made by Afschrift *et al.*, where they stated that the results' quality was very slightly affected, whether a constant gain was used to describe the ankle strategy or not. With an average decrease of 0.08 of R^2 for the goodness of the fit for the ankle joints, we hypothesized that this deflection could be neglected and use constant gains[3] throughout the entire simulations[82].

3.3.5 Comparative study

As previously stated, the direct comparative study with the experimental data being compromised, we mainly assessed our controller via the NMM itself. Indeed, even if the simulation does not track efficiently the studied experimental data of Chapter 2, Geyer showed that the ankle torque behavior produced by the NMM matched quasi unequivocally the trajectory of the joint produced during a human steady state walking. Therefore, we will assess the ability of the NMM to generate a human-like response to a

[3] $K_p = -1.07$ and $K_v = -0.61$ for the feedback constant gain values relative to the position and the velocity respectively. These values where taken from Table 2.4.

perturbation via a general graphical comparison and evaluate, the need and contribution, of a reactive balance ankle controller.

3.4 Results

In this section, we will merge our results with the ones obtained experimentally graphically, in order to assess the reactive balance response of the NMM and the contribution of our delayed COM feedback controller on it. For the rest of the thesis, we presented the plantar-flexion as a decrease of the torque whereas the dorsi-flexion as an increase (different conventions that the ones presented in Geyer's results).

3.4.1 Model response to a pelvic perturbation

First, we assessed the response of the NMM to different pelvic perturbation amplitudes to confirm the lack of reactive balance control adjustment of the ankle, as showed by various authors [88][89][110]. The different computational results have been plotted on the left side in Figure 3.7, whereas the human responses are presented on the right side.

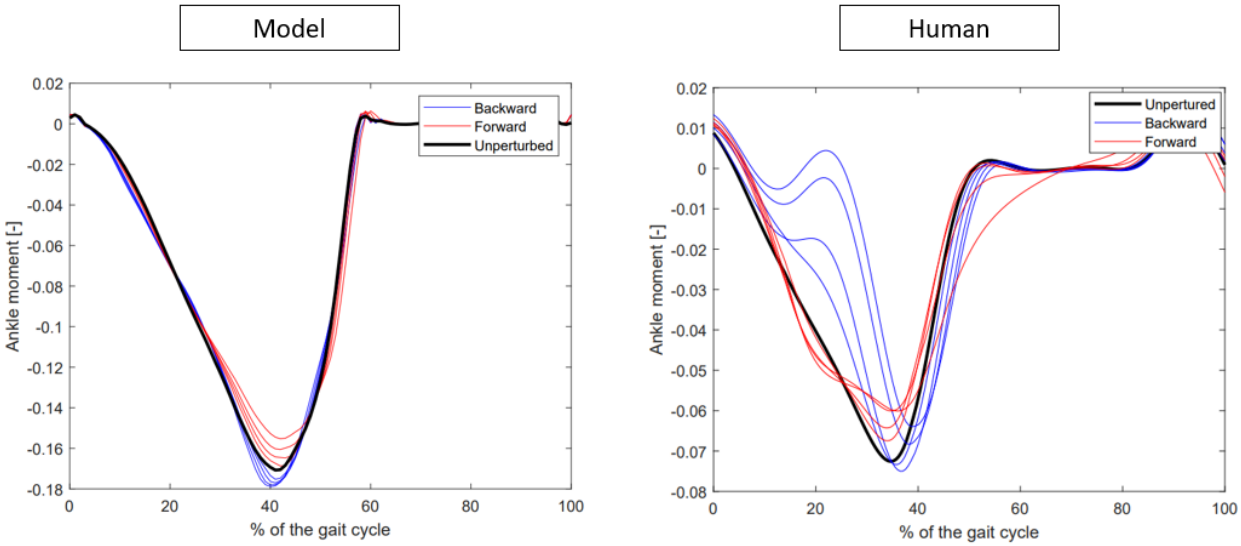


Figure 3.7: Left - Computational model ankle joints in response to various pelvic perturbation magnitudes. Right - Human ankle joints in response to various pelvic perturbation magnitudes.

Visually, we can confirm a lack in the simulated model attempt to provide human-like ankle adjustment, in response to pelvic perturbation. Indeed, during a backward perturbation (blue), the ankle should respond with an initial dorsiflexion followed by a pronounced drop, to finally get back to an unperturbed behavior, as we can see on human experimental data. Moreover, the chart shows that during a forward perturbation (red), a plantarflexion shortage, compared to the unperturbed trajectory, should be observed before restoring to its initial state. While for the simulated ankle moments, the curve presents an opposite accentuated plantarflexion in response to backward perturbations. However, it presents the weaker plantarflexion in response to a forward perturbation.

Different authors tried to follow a data driven approach by re-optimizing the reflex-model parameters, by removing the forward rigid body dynamics and injecting real experimental data in order to evaluate if this lack of human-like behavior was due to the neuromuscular model control in itself or to the rigid body dynamics. Brug *et al.*, showed that even with re-optimized parameters, the simulation model was unable to generate human-like ankle moments in response to pelvic perturbation translating a gap in the neuromuscular model regarding reactive balance responses [110].

Geyer's neuromuscular model uses local reflex signals for the muscular activation of the forward rigid body. The absence of a central pattern generator, responsible for task-level modulation, could be the reason behind the NMM disability to reach human like pattern, in response to AP alterations. Moreover, we confirmed in Chapter 2, that ankle moments adjustment sensorimotor transformation at 250 $[ms]$, after the onset of perturbation were rising from task-level variables. Therefore, the addition of a layer of control underlying CPG principles, to the reflex-based model, is justified.

3.4.2 Contribution of the controller

3.4.3 Experimental perturbation amplitude

In order to assess the potential added value of an additional COM delayed feedback controller in the neuromuscular model, where the ankle adjustment during the ankle strategy is inhibited, we used zero lag cross-correlation indicators. Indeed, as we did not optimise the original reflex parameters of the model, the amplitude differences would bias our results. To do so, we pooled our data for backward and forward perturbation and simulated the different statistical features with the additional COM control in Table 3.2. First, we can see that the values are very close between the original and the adapted NMM. Indeed, without an optimisation of the NMM parameters and data driven inputs, the added reactive torque relative to the behavior of a rigid body responses. Besides the closeness of the results, statistical tools show an infinitesimal enhancement tendency of the adapted NMM to produce more human-like ankle responses after a sagittal perturbation, compared to the original NMM.

3.4.4 Extreme perturbation amplitudes

The results above show us that the the bio-mechanical parameters fitted for humans can not be directly used to fit the behavior of a rigid body, in response to a perturbation. To allow the assessment of the controller itself, we should use the neuromuscular model as a controller in itself where the inputs, would not be rigid body movements and contacts, but real human movements that would be directly sent to the body sensors of the neuromuscular model, as proposed by Keemink *it* [88]. This drawback prevented us from assessing efficiently our controller, as the produced inputs by the rigid body in response to a perturbation are not comparable with the ones produced by a real human.

Nevertheless, for more insights, we tried to fit the COM feedback model on the rigid body moments data, by tuning the different gains to see if this model could prevent a fall of the virtual body. First, we looked at which percentage of the body weight, a fall of the rigid body could be induced. By trial an error, we found that a magnitude of 38% would

Table 3.2: Summary of normalised cross-correlations and RMSE values of the difference between Geyer's original and adapted model, and Vlutters experimental data (pooled) joint moments for backward and forward perturbation for a walking velocity of 1.25 $[m/s]$.

Speed: 1.25 [m/s]	Original model		Adapted model	
	Backward	*Forward*	*Backward*	*Forward*
R	0.90	0.85	0.91	0.85
RMSE	0.0579	0.0546	0.0578	0.0545

lead to a fall of the virtual body. Secondly, we tested different values of gains but none of them seemed to prevent the fall through the COM model.

3.5 Discussion

In this section we will present the different insights that our study has shown compared to other authors and shows the interesting properties that a neuromuscular model could add to active prosthetic and orthotic (P/O) devices.

3.5.1 Reflex-based neuromuscular model with additional COM feedback

Thanks to our research we found that for the assessment of our controller, via a neuromuscular model, an optimization and a change of the rigid body movements was needed in order to reach global human-like behavior. Moreover, other authors found that an optimization of the parameters and a change of movement inputs alone, was not sufficient to mimic a human like behavior in response to an alteration. The neuromuscular model lacked of a process to provide reactive balance reactions. A solution could lie in COM feedback model.

After the discovery of Afschrift and his team, that ankle moments could be predicted by the center of mass kinematics, they also tested its efficiency on Geyer's neuromuscular model of 2010 [89]. Contrary to our study, Afschrift *et al.*, anticipated the mismatches between the rigid body and the COM model parameters, by using a data-driven approach with inverse kinematics as inputs of the NMM and an optimization of the reflex parameters to reach responses in agreement with experimental data. Moreover, they tested an experimental data sets where the subjects were perturbed by treadmill belts accelerations. Thanks to an additional optimisation of the feedback gains and to the implementation of their delayed COM model, they showed an improvement in the human-like outputs of the

computation model where the graphical goodness of the fit, towards experimental data, was enhanced. These encouraging results, ensure our hypothesis that our results would have been similar to the article with this data driven approach. Moreover, it strengthens the hypothesis that additional CPG complexes would fill the voids of the reflex-based NMM. Dzeladini *et al.*, already showed that adding a CPG to the computational model, brought a control of locomotion speed [116].

With our work we wanted to generalize Afschrift *et al.* conclusions, by testing a different perturbation. Indeed, we used the pooled gains from Chapter 2, to test if the possibility to have two common gains (relative to the position and the velocity) could be a plausible future outcome independent on the sagittal perturbation type. However, future works of the authors aim at testing the robustness of the COM model against different sagittal perturbations. Moreover, we wanted to show that the relationship relating the COM to the ankle (cf. eq 2.1) could directly predict reactive behavior, as Afschrift *et al.* tested the equation relating the COM and to the muscle activities.

3.5.2 P/O devices

Through this chapter, we have seen that using Geyer's neuromuscular model by itself, is not the most appropriate tool to assess a controller due to its rigid body inputs. More and more, such neuromuscular models are incorporated as controllers (cf. section 1.4.2) for active prosthetic and orthotic (P/O) devices. Indeed, in predefined trajectories controllers[4], neuromuscular model could contribute broadly. By enhancing the neuromuscular responses to reach the most human-like behavior in various events (i.e. different grounds, perturbations, etc.), the controller will be able to provide different control outputs assistance for a broader range of environment, without needing various experimental records. Therefore, making the NMM more robust against different situation, would be a key to enhance actual P/O assistive devices. Consequently, neuromuscular models of bipedal locomotion aid understanding underlying neural processes during locomotion and are tools that could be easily adaptable to orthoses controllers.

3.6 Conclusion

In this chapter, we tried assessing the ability of our COM model based controller to bring reactive balance assistance in an inhibited balance NMM. Unfortunately, the non data-driven approach regarding the inputs of the simulations and the non optimization of the reflex-based parameters, led us to biased results preventing us to have an effective evaluation of our COM model.

Thanks to additional scientific literature researches, we still believe that the COM delayed feedback model could be a potential orthosis controller for the ankle. Moreover, Geyer's neuromuscular model disability to provide human-like reactive balance control in sagittal plane, could be explained by the lack of a central pattern generator. Muscular reflexes seem to be insufficient for such a control.

[4] *Under a predefined gait trajectory control mechanism, the desired joint trajectory is pre-recorded from a healthy person (...) and then replayed on an exoskeleton. To improve usability and flexibility of the controller, the desired joint trajectory is usually parameterized according to different postures.* [79]

Limitations

This second part of the study, comes with some strong limitations. Indeed, we did not anticipate the behavior of the NMM without optimisation of its reflex parameters and without the data driven inputs.

First, the fact that the inputs are the rigid body movements, lead to a biased analysis of the outputs for our study. Indeed, the bio-mechanical interactions parameters of such a body differ from the ones of a real human body. To cope with this default, data driven inputs should be provided to the NMM by removing the rigid body dynamics.

Second, in order to ensure that the data-driven inputs generate human-like outputs comparable with experimental data, an optimisation of the reflex parameters of the NMM is needed. By minimizing the differences between the comparative experimental set results and the computational model values for the different parameters of the reflex model, a more subject-like behavior can be obtained. It seems that most of the authors working with Geyer's neuromuscular model used the covariance matrix adaptation evolution strategy (CMAES) for this optimisation. The simulation time of such an optimisation can rise from 15h to 20h. Therefore, we tested some basic Matlab integrated optimisation tools, but they did not lead to any reliable results.

Conclusion and perspectives

To conclude this thesis, we will expose the most relevant conclusions we made all over the realisation of this study. Moreover we will present potential perspectives towards which the project could evolve.

General conclusions

Throughout this thesis we proposed a potential mid-level ankle joint orthosis controller for reactive balance purposes. Thanks to a model fitting on experimental data, we confirmed the efficiency of the model at a discrete time instance. Unfortunately, the assessment of the model-based controller via a neuromuscular reflex-based simulation did not lead to any significant progress.

In the first chapter, we began with an overview of important concepts about balance control, in order to better understand the underlying systems that a bio-inspired controller could use as inspiration. Thanks to this global approach, we learnt that balance control was a neural problem and therefore that inputs involved in the neuronal system should be considered for our purpose.

In the second chapter, the main objective was to find and assess, a bio-inspired model able to fit reactive balance experimental data. Based on the conclusions of the first chapter, we found two bio-inspired models, the COM feedback model and the local joint feedback model, that could have the ability to respond to our needs. Throughout linear least-squares regression, results at discrete time instances were evaluated in order to assess the different fits of the studied models. By using different statistical tools, we reproduced scientific literature conclusions, by presenting encouraging results, for the COM feedback model relative to the ankle joints, in response to anterior/posterior sagittal perturbation at two different speeds. The results for the knee and the hip joints, were significantly different, enabling us to state some hypothesis on plausible sensorimotor transformation underlying reactive balance of lower limb joints.

In the last chapter, we attempt at assessing a COM feedback delayed model-based controller, via a neuromuscular reflex-based simulation. To do so, we added some additional blocks to the computational model (perturbation and controller blocks), in order to have a platform with similar conditions than the ones tested experimentally. Due to a lack of anticipation, optimisations and input constraints restricted us in the global assessment of our controller and did not gave us any significant new insights. Thanks to this chapter, we learnt that Geyer's neuromuscular model was more appropriate as a controller than

as a simulation platform, due to the rigid body dynamics driving the bipedal locomotion model. Nevertheless, different scientific articles, where Geyer's model was used as a controller, proved that there was a dysfunction in the neuromuscular model relative to its reaction toward sagittal anterior/posterior perturbations. Moreover, encouraging findings show that the addition of CPG derived controls, enhances the reduced human-like reactive balance response of the reflex-model.

Perspectives

These different drawn conclusions, encourages the possibility to have a delayed COM feedback model-based controller as a potential candidate for future rehabilitation applications, as active orthosis. To have an idea of such implementation, we proposed a feasible controller architecture in Figure 3.8. For the different feedback gains, common gains for all the wearers could be used, as the reconstruction ability is not significantly decreased, as proved in chapter 2. A broader range of sagittal perturbations should be taken into account, to provide an assistance for the largest possible scope. The second needed inputs are the reference center-of-mass kinematics. An approach to be considered, could lie in the incorporation of a data driven neuromuscular model which would ensure a follow up, of a reference trajectory, in a synchronized fashion with the locomotion rhythms of the orthosis wearer. For the altered trajectory, direct measures from sensors would be more adequate. Nevertheless, the COM kinematics follow up is not the easiest kinematic to measure out of laboratory environments. Therefore, an alternative to 3D motion analysis or to force platforms have to be found. Some authors proposed COM estimations throughout portable sensors in order to cope with this drawback [117].

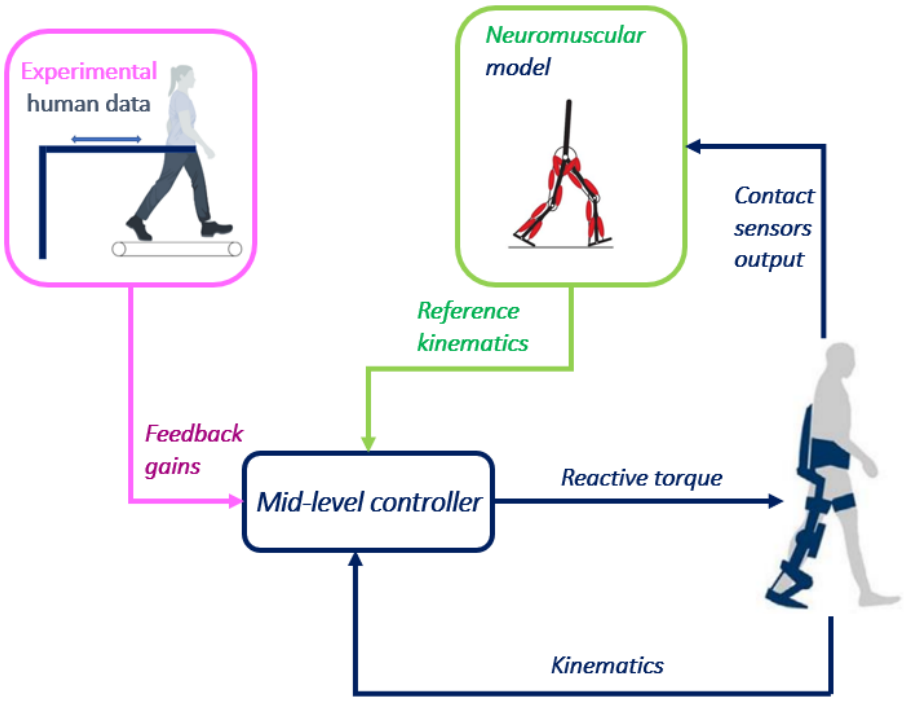


Figure 3.8: Potential controller external architecture.

Currently, an active hip orthosis is developed at UCLouvain and could be used for future mid-level balance assistive controllers implementations. A better understanding of the sensorimotor transformations underlying the knee and the hip joints responses, would open the path towards orthoses providing reactive balance assistance through the three lower limb joint, in a human like manner.

Bibliography

[1] CDC (2021). Facts About Falls. Centers for Disease Control and Prevention, National Center for Injury Prevention and Control. https://www.cdc.gov/falls/facts.html

[2] Hayes, W. C., Myers, E. R., Morris, J. N., Gerhart, T. N., Yett, H. S., & Lipsitz, L. A. (1993). Impact near the hip dominates fracture risk in elderly nursing home residents who fall. Calcified tissue international, 52(3), 192-198.

[3] Jager, T. E., Weiss, H. B., Coben, J. H., & Pepe, P. E. (2000). Traumatic brain injuries evaluated in US emergency departments, 1992 [U+2010] 1994. Academic Emergency Medicine, 7(2), 134-140.

[4] Florence, C. S., Bergen, G., Atherly, A., Burns, E., Stevens, J., & Drake, C. (2018). Medical costs of fatal and nonfatal falls in older adults. Journal of the American Geriatrics Society, 66(4), 693-698.

[5] Boelens, C., Hekman, E. E., & Verkerke, G. J. (2013). Risk factors for falls of older citizens. Technology and Health care, 21(5), 521-533.

[6] Stroke Association (n.d.) Balance problems after stroke. https://www.stroke.org.uk/eV8

[7] Seth, M., & Lamberg, E. (2017). Standing balance in people with trans-tibial amputation due to vascular causes: A literature review. Prosthetics and Orthotics International, 41(4), 345-355.

[8] Dunning, K., LeMasters, G., & Bhattacharya, A. (2010). A major public health issue: the high incidence of falls during pregnancy. Maternal and child health journal, 14(5), 720-725.

[9] Bateni, H., & Maki, B. E. (2005). Assistive devices for balance and mobility: benefits, demands, and adverse consequences. Archives of physical medicine and rehabilitation, 86(1), 134-145.

[10] Dollar, A. M., & Herr, H. (2007, June). Active orthoses for the lower-limbs: challenges and state of the art. In 2007 IEEE 10th International Conference on Rehabilitation Robotics (pp. 968-977). IEEE.

[11] Kurz, I., Gimmon, Y., Shapiro, A., Debi, R., Snir, Y., Melzer, I. (2016). Unexpected perturbations training improves balance control and voluntary stepping times in older adults-a double blind randomized control trial. BMC geriatrics, 16(1), 1-11.

[12] Whittle, M. W. (2014). Gait analysis: an introduction. Butterworth-Heinemann.

[13] MacConaill, M. A. (2020, November 2). joint. Encyclopedia Britannica. https://www.britannica.com/science/joint-skeleton

[14] Burnfield, J. M., Josephson, K. R., Powers, C. M., Rubenstein, L. Z. (2000). The influence of lower extremity joint torque on gait characteristics in elderly men. Archives of physical medicine and rehabilitation, 81(9), 1153-1157.

[15] Dimon, T. (2001). Anatomy of the moving body: a basic course in bones, muscles, and joints. North Atlantic Books.

[16] Sloot, L. H., Van der Krogt, M. M. (2018). Interpreting joint moments and powers in gait. In Handbook of Human Motion (pp. 625-643). Springer International Publishing AG.

[17] Anand, A. S., Zhao, G., Roth, H., Seyfarth, A. (2019, October). A deep reinforcement learning based approach towards generating human walking behavior with a neuromuscular model. In 2019 IEEE-RAS 19th International Conference on Humanoid Robots (Humanoids) (pp. 537-543). IEEE.

[18] TeachMe Series (2022), Muscles of the Lower Limb https://teachmeanatomy.info/lower-limb/muscles/

[19] Pirker, W., Katzenschlager, R. (2017). Gait disorders in adults and the elderly. Wiener Klinische Wochenschrift, 129(3), 81-95.

[20] Kharb, A., Saini, V., Jain, Y. K., Dhiman, S. (2011). A review of gait cycle and its parameters. IJCEM International Journal of Computational Engineering & Management, 13, 78-83.

[21] Tekscan (n.d.), The Gait Cycle: Phases, Parameters to Evaluate Technology https://www.tekscan.com/blog/medical/gait-cycle-phases-parameters-evaluate technology#:~:text=The%20stance%20phase%20of%20gait,foot%20touches%20the%20ground%20again.

[22] Webster, J. B., & Darter, B. J. (2019). Principles of normal and pathologic gait. In Atlas of Orthoses and Assistive Devices (pp. 49-62). Elsevier.

[23] Berke, G. M., Buell, N., Fergason, J., Gailey, R., Hafner, B., Hubbard, S., & Willingham, L. (2008). Transfemoral Amputation: The Basic and Beyond. Prosthetics Research Study.

[24] Reimann, H., Fettrow, T., & Jeka, J. J. (2018). Strategies for the control of balance during locomotion. Kinesiology Review, 7(1), 18-25.

[25] Pollock, A. S., Durward, B. R., Rowe, P. J., Paul, J. P. (2000). What is balance?. Clinical rehabilitation, 14(4), 402-406.

[26] Winter, D. A. (1995). Human balance and posture control during standing and walking. Gait posture, 3(4), 193-214.

[27] Purves D, Augustine GJ, Fitzpatrick D, et al. (2001). Chapter 14, The Vestibular System. Neuroscience. 2nd edition. Sunderland (MA): Sinauer Associates https://www.ncbi.nlm.nih.gov/books/NBK10819/

[28] Shaffer, S. W., Harrison, A. L. (2007). Aging of the somatosensory system: a translational perspective. Physical therapy, 87(2), 193-207.

[29] Woollacott, M. H., Tang, P. F. (1997). Balance control during walking in the older adult: research and its implications. Physical therapy, 77(6), 646-660.

[30] Wang, Y., Srinivasan, M. (2014). Stepping in the direction of the fall: the next foot placement can be predicted from current upper body state in steady-state walking. Biology letters, 10(9), 20140405.

[31] Health and Physical Education Standards (n.d.) Physical Education Glossary https://www.k12.wa.us/sites/default/files/public/healthfitness/standards/physicaleducationtermsglossary.pdf

[32] Patla, A. E. (1993). Age-related changes in visually guided locomotion over different terrains: major issues. In Sensorimotor impairment in the elderly (pp. 231-252). Springer, Dordrecht

[33] Patla AE, Prentice S, Robinson C, Neufeld J. Visual control of locomotion: strategies for changing direction and for going over obstacles. JExp Psychol Hum Percept Perjonn. 1991;17:603-634..

[34] Patla AE, Rietdyk S. Visual control of limb trajectory over obstacles during locomotion: effect of obstacle height and width. Gait and Posture. 1993;1:45-60.

[35] Patla AE, Robinson C, Samways M, Armstrong CJ. Visual control of step length during overground locomotion: task-specific modulation of the locomotor synergy. JExp Psychol Hum Percppt Pmform. 1989;15: 603-617.

[36] Chen H-C, Ashton-Miller JA, Alexander NB, Schultz AB. Stepping over obstacles: gait patterns of healthy young and old adults. J Gerontol. 1991;46:M196-M203.

[37] Chen H-C, Ashton-Miller JA, Alexander NB. Schultz AB. Effects of age and variable response time on ability to step over an obstacle. J Gerontol. 1994;49:M227-M233

[38] Chen H-C, Schultz AB, Ashton-Miller JA, et al. Stepping over obstacles: dividing attention impairs performance of old more than young adults. J Gerontol. 1996;51 :M116-M122.

[39] Blenkinsop, G. M., Pain, M. T., Hiley, M. J. (2017). Balance control strategies during perturbed and unperturbed balance in standing and handstand. Royal Society open science, 4(7), 161018.

[40] Hof, A. L. (2007). The equations of motion for a standing human reveal three mechanisms for balance. Journal of biomechanics, 40(2), 451-457.

[41] Halvorsen, K. (2010). Comments on "The equations of motion for a standing human reveal three mechanisms for balance"(A. Hof, Vol. 40, pp. 451–457). Journal of biomechanics, 16(43), 3244-3247.

[42] Binder, M.D., Hirokawa, N., Windhorst, U. (2009). Stepping Strategy. Encyclopedia of Neuroscience. Springer, Berlin, Heidelberg.

[43] Van Wouwe, T., Afschrift, M., Dalle, S., Van Roie, E., Koppo, K., De Groote, F. (2021). Adaptations in Reactive Balance Strategies in Healthy Older Adults After a 3-Week Perturbation Training Program and After a 12-Week Resistance Training Program. Frontiers in Sports and Active Living, 3, 714555.

[44] Jamshidi, N., Rostami, M., Najarian, S., Menhaj, M. B., Saadatnia, M., Salami, F. (2010). Differences in center of pressure trajectory between normal and steppage gait. Journal of research in medical sciences: the official journal of Isfahan University of Medical Sciences, 15(1), 33.

[45] WIKIPEDIA (2018) Center of pressure (terrestrial locomotion) https://en.wikipedia.org/wiki/Center_of_pressure_(terrestrial_locomotion)

[46] Nashner, L. M. (1980). Balance adjustments of humans perturbed while walking. Journal of neurophysiology, 44(4), 650-664.

[47] Tang, P. F., Woollacott, M. H. (1999). Phase-dependent modulation of proximal and distal postural responses to slips in young and older adults. Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences, 54(2), M89-M102.

[48] Ferber, R., Osternig, L. R., Woollacott, M. H., Wasielewski, N. J., Lee, J. H. (2002). Reactive balance adjustments to unexpected perturbations during human walking. Gait posture, 16(3), 238-248.

[49] Hof, A. L., Duysens, J. (2013). Responses of human hip abductor muscles to lateral balance perturbations during walking. Experimental brain research, 230(3), 301-310.

[50] Afschrift, M., van Deursen, R., De Groote, F., Jonkers, I. (2019). Increased use of stepping strategy in response to medio-lateral perturbations in the elderly relates to altered reactive tibialis anterior activity. Gait posture, 68, 575-582.

[51] Hof, A. L., Vermerris, S. M., Gjaltema, W. A. (2010). Balance responses to lateral perturbations in human treadmill walking. Journal of Experimental Biology, 213(15), 2655-2664.

[52] Welch, T. D., Ting, L. H. (2009). A feedback model explains the differential scaling of human postural responses to perturbation acceleration and velocity. Journal of neurophysiology, 101(6), 3294-3309.

[53] Reimann, H., Fettrow, T. D., Thompson, E. D., Agada, P., McFadyen, B. J., Jeka, J. J. (2017). Complementary mechanisms for upright balance during walking. PloS one, 12(2), e0172215.

[54] Vlutters, M., Van Asseldonk, E. H., Van der Kooij, H. (2016). Center of mass velocity-based predictions in balance recovery following pelvis perturbations during human walking. Journal of experimental biology, 219(10), 1514-1523.

[55] Jacquelin Perry, M. D. (1992). Gait analysis: normal and pathological function. New Jersey: SLACK.

[56] Warlow, C. P. (1998). Epidemiology of stroke. The Lancet, 352, S1-S4.

[57] Feigin, V. L., Brainin, M., Norrving, B., Martins, S., Sacco, R. L., Hacke, W., ... Lindsay, P. (2022). World Stroke Organization (WSO): global stroke fact sheet 2022. International Journal of Stroke, 17(1), 18-29.

[58] Belgian Stroke Council (n.d.). Reconnaître à temps les symptômes d'un AVC, c'est sauver des vies.
http://reconnaitreunavc.be/

[59] Wolfe, C. D. (2000). The impact of stroke. British medical bulletin, 56(2), 275-286.

[60] Patterson, K. K., Gage, W. H., Brooks, D., Black, S. E., McIlroy, W. E. (2010). Changes in gait symmetry and velocity after stroke: a cross-sectional study from weeks to years after stroke. Neurorehabilitation and Neural Repair, 24(9), 783-790.

[61] Patterson, K. K., Parafianowicz, I., Danells, C. J., Closson, V., Verrier, M. C., Staines, W. R., ... McIlroy, W. E. (2008). Gait asymmetry in community-ambulating stroke survivors. Archives of physical medicine and rehabilitation, 89(2), 304-310.

[62] Pollock, C., Eng, J., Garland, S. (2011). Clinical measurement of walking balance in people post stroke: a systematic review. Clinical Rehabilitation, 25(8), 693-708.

[63] Tyson, S. F., Kent, R. M. (2013). Effects of an ankle-foot orthosis on balance and walking after stroke: a systematic review and pooled meta-analysis. Archives of physical medicine and rehabilitation, 94(7), 1377-1385.

[64] Zane, M. K. (2018). American Physical Therapy Association (APTA): Physical Therapy Guide to Above-Knee Amputation (Transfemoral Amputation) https://www.choosept.com/guide/physical-therapy-guide-above-knee-amputation#:~:text=Transfemoral%20(above%20knee)%20amputation%20is,%2C%20disease%2C%20or%20congenital%20defect.

[65] Fanciullacci, C., McKinney, Z., Monaco, V., Milandri, G., Davalli, A., Sacchetti, R., ... & Gruppioni, E. (2021). Survey of transfemoral amputee experience and priorities for the user-centered design of powered robotic transfemoral prostheses. Journal of neuroengineering and rehabilitation, 18(1), 1-25.

[66] Sanz-Morere, C. B., Fantozzi, M., Parri, A., Giovacchini, F., Baldoni, A., Cempini, M., ... & Vitiello, N. (2019). A knee–ankle–foot orthosis to assist the sound limb of transfemoral amputees. IEEE Transactions on Medical Robotics and Bionics, 1(1), 38-48.

[67] Lamoth, C. J., Ainsworth, E., Polomski, W., & Houdijk, H. (2010). Variability and stability analysis of walking of transfemoral amputees. Medical engineering physics, 32(9), 1009-1014.

[68] World Bank Group. (2022).Population ages 65 and above, total.
https://data.worldbank.org/indicator/SP.POP.65UP.TO?end=2021&most_recent_value_desc=false&start=1960&view=chart

[69] Moylan, K. C., Binder, E. F. (2007). Falls in older adults: risk assessment, management and prevention. The American journal of medicine, 120(6), 493-e1.

[70] Nnodim, J. O., Yung, R. L. (2015). Balance and its clinical assessment in older adults–a review. Journal of geriatric medicine and gerontology, 1(1).

[71] Moylan, K. C., Binder, E. F. (2007). Falls in older adults: risk assessment, management and prevention. The American journal of medicine, 120(6), 493-e1.

[72] Woollacott, M. H. (2000). Systems contributing to balance disorders in older adults. The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 55(8), M424-M428.

[73] Aboutorabi, A., Bahramizadeh, M., Arazpour, M., Fadayevatan, R., Farahmand, F., Curran, S., Hutchins, S. W. (2016). A systematic review of the effect of foot orthoses and shoe characteristics on balance in healthy older subjects. Prosthetics and orthotics international, 40(2), 170-181.

[74] Gross, M. T., Mercer, V. S., Lin, F. C. (2012). Effects of foot orthoses on balance in older adults. Journal of orthopaedic sports physical therapy, 42(7), 649-657.

[75] Herr, H. (2009). Exoskeletons and orthoses: classification, design challenges and future directions. Journal of neuroengineering and rehabilitation, 6(1), 1-9.

[76] International Organization for Standardization. (2020). Prosthetics and orthotics — Vocabulary — Part 3: Terms relating to orthoses (ISO 8549). https://www.iso.org/obp/ui/#iso:std:iso:8549:-3:ed-2:v1:en

[77] Jain, V. (2021). Types of Controllers | Proportional Integral and Derivative Controllers. Electrical 4U. https://www.electrical4u.com/types-of-controllers-proportional-integral-derivative controllers/#:~:text=In%20control%20systems%2C%20a%20controller,in%20all% 20complex%20control%20systems.

[78] Baud, R., Manzoori, A. R., Ijspeert, A., & Bouri, M. (2021). Review of control strategies for lower-limb exoskeletons to assist gait. Journal of NeuroEngineering and Rehabilitation, 18(1), 1-34.

[79] T. Yan, M. Cempini, C. M. Oddo, and N. Vitiello, "Review of assistive strategies in powered lower-limb orthoses and exoskeletons," Robotics Autonomous Syst., vol. 64, pp. 120–136, 2015.

[80] Wang, S., Wang, L., Meijneke, C., Van Asseldonk, E., Hoellinger, T., Cheron, G., ... & Van Der Kooij, H. (2014). Design and control of the MINDWALKER exoskeleton. IEEE transactions on neural systems and rehabilitation engineering, 23(2), 277-286.

[81] Ugurlu, B., Oshima, H., & Narikiyo, T. (2014, May). Lower body exoskeleton-supported compliant bipedal walking for paraplegics: How to reduce upper body effort?. In 2014 IEEE international conference on robotics and automation (ICRA) (pp. 1354-1360). IEEE.

[82] Afschrift, M., De Groote, F., Jonkers, I. (2021). Similar sensorimotor transformations control balance during standing and walking. PLoS computational biology, 17(6), e1008369.

[83] Emmens, A. R., Van Asseldonk, E. H., Van Der Kooij, H. (2018). Effects of a powered ankle-foot orthosis on perturbed standing balance. Journal of neuroengineering and rehabilitation, 15(1), 1-13.

[84] Miller, R.H. (2018). Hill-Based Muscle Modeling.Handbook of Human Motion. Springer, Cham.

[85] The biomechanics of human skeletal muscle. Hall S.J.(Ed.), (2015). Basic Biomechanics, 7e. McGraw Hill.

[86] Thatte, N. Geyer, H. Toward Balance Recovery with Leg Prostheses using Neuromuscular Model Control. IEEE Trans Biomed Eng, doi: 10.1109/TBME.2015.2472533 (2015).

[87] Geyer, H., Thatte, N., Duan, H. (2017). Toward Balance Recovery with Active Leg Prostheses Using Neuromuscular Model Control. In Converging Clinical and Engineering Research on Neurorehabilitation II (pp. 649-652). Springer, Cham.

[88] Keemink, A. Q. L., Brug, T. J. H., Van Asseldonk, E. H. F., Wu, A. R., Van Der Kooij, H. (2021). Whole body center of mass feedback in a reflex-based neuromuscular model predicts ankle strategy during perturbed walking. IEEE transactions on neural systems and rehabilitation engineering, 29, 2521-2529.

[89] Afschrift, M., Groote, F. D. (2020, October). Reflex-Model with Additional COM Feedback Describes the Ankle Strategy in Perturbed Walking. In International Symposium on Wearable Robotics (pp. 69-73). Springer, Cham.

[90] Buchli, J., Righetti, L., & Ijspeert, A. (n.d.) Adaptive Frequency Oscillators. EPFL. https://www.epfl.ch/labs/biorob/research/neuromechanical/page-36365-en-html/#:~:text=Our%20first%20attempt%20toward%20adaptive,of%20any%20periodic%20input%20signal.

[91] Monaco, V., Tropea, P., Aprigliano, F., Martelli, D., Parri, A., Cortese, M., ... & Micera, S. (2017). An ecologically-controlled exoskeleton can improve balance recovery after slippage. Scientific reports, 7(1), 1-10.

[92] Van der Noot, N., Ijspeert, A. J., Ronsse, R. (2018). Bio-inspired controller achieving forward speed modulation with a 3D bipedal walker. The International Journal of Robotics Research, 37(1), 168-196.

[93] Vlutters, M., van Asseldonk, E. H., & van der Kooij, H. (2018). Lower extremity joint-level responses to pelvis perturbation during human walking. Scientific reports, 8(1), 1-12.

[94] Delp, S. L., Anderson, F. C., Arnold, A. S., Loan, P., Habib, A., John, C. T., ... & Thelen, D. G. (2007). OpenSim: open-source software to create and analyze dynamic simulations of movement. IEEE transactions on biomedical engineering, 54(11), 1940-1950.

[95] Safavynia, S. A., Ting, L. H. (2013). Long-latency muscle activity reflects continuous, delayed sensorimotor feedback of task-level and not joint-level error. Journal of neurophysiology, 110(6), 1278-1290.

[96] Ting, L. H., van Antwerp, K. W., Scrivens, J. E., McKay, J. L., Welch, T. D., Bingham, J. T., & DeWeerth, S. P. (2009). Neuromechanical tuning of nonlinear postural control dynamics. Chaos: An Interdisciplinary Journal of Nonlinear Science, 19(2), 026111.

[97] Ting, L. H., van Antwerp, K. W., Scrivens, J. E., McKay, J. L., Welch, T. D., Bingham, J. T., DeWeerth, S. P. (2009). Neuromechanical tuning of nonlinear postural control dynamics. Chaos: An Interdisciplinary Journal of Nonlinear Science, 19(2), 026111.

[98] Torrie, J. H. (1960). Principles and procedures of statistics: with special reference to the biological sciences. McGraw-Hill.

[99] Stephanie Glen. (n.d.). RMSE: Root Mean Square Error. StatisticsHowTo.com: Elementary Statistics for the rest of us! https://www.statisticshowto.com/probability-and-statistics/regression-analysis/rmse-root-mean-square-error/

[100] (n.d.). SPSS TUTORIALS: PAIRED SAMPLES T TEST. Kent State University. https://libguides.library.kent.edu/spss/pairedsamplesttest#:~:text=The%20Paired%20Samples%20t%20Test,between%20the%20two%20time%20points)

[101] Welch, T. D., & Ting, L. H. (2008). A feedback model reproduces muscle activity during human postural responses to support-surface translations. Journal of neurophysiology, 99(2), 1032-1038.

[102] Cherry, K. (2022). What is correlation? Verywellmind. https://www.verywellmind.com/what-is-correlation-2794986

[103] Allen, J. L., & Ting, L. H. (2016). Why is neuromechanical modeling of balance and locomotion so hard?. In Neuromechanical modeling of posture and locomotion (pp. 197-223). Springer, New York, NY.

[104] Klarner, T., & Zehr, E. P. (2018). Sherlock Holmes and the curious case of the human locomotor central pattern generator. Journal of neurophysiology, 120(1), 53-77.

[105] Daley, M. A., Felix, G., & Biewener, A. A. (2007). Running stability is enhanced by a proximo-distal gradient in joint neuromechanical control. Journal of Experimental Biology, 210(3), 383-394.

[106] Nataraj, R., Audu, M. L., Triolo, R. J. (2012). Comparing joint kinematics and center of mass acceleration as feedback for control of standing balance by functional neuromuscular stimulation. Journal of neuroengineering and rehabilitation, 9(1), 1-11.

[107] Kerckhofs, G. (2021). Tissue Engineering LGBIO2071 - Course 6: Modelling. Université Catholique de Louvain (UCLouvain). Louvain-la-Neuve, Belgium.

[108] Mallet, D. G. (2012). In silico experimental modeling of cancer treatment. International Scholarly Research Notices, 2012.

[109] Geyer, H. (n.d.). Impact on Human Motor Control: Systematic expansion into neuromuscular human model that encodes principles of legged mechanics. https://www.cs.cmu.edu/~hgeyer/Software/Neuromuscular%20Model/Geyer%20Neuromuscular%20Model.zip

[110] Brug, T. J. H., Keemink, A. Q. L., van Asseldonk, E. H. F., & van der Kooij, H. (2017, June). A First Step Towards Adapting the 3D Reflex Based Neuromuscular Gait Model for Gait Assistive Devices. In Dynamic Walking 2017: Principles and Concepts of Legged Locomotion.

[111] Geyer, H., & Herr, H. (2010). A muscle-reflex model that encodes principles of legged mechanics produces human walking dynamics and muscle activities. IEEE Transactions on neural systems and rehabilitation engineering, 18(3), 263-273.

[112] Rybak, I. A., Shevtsova, N. A., Lafreniere [U+2010] Roula, M., & McCrea, D. A. (2006). Modelling spinal circuitry involved in locomotor pattern generation: insights from deletions during fictive locomotion. The Journal of physiology, 577(2), 617-639.

[113] Pearson, K. A. J. G., Gordon, J. (2000). Spinal reflexes. Principles of neural science, 4, 713-736.

[114] Lakna (2020). What is the difference between hip and pelvis. PEDIAA. https://pediaa.com/what-is-the-difference-between-hip-and-pelvis/

[115] Spiess, A. N., Neumeyer, N. (2010). An evaluation of R2 as an inadequate measure for nonlinear models in pharmacological and biochemical research: a Monte Carlo approach. BMC pharmacology, 10(1), 1-11.

[116] Dzeladini, F., Van Den Kieboom, J., & Ijspeert, A. (2014). The contribution of a central pattern generator in a reflex-based neuromuscular model. Frontiers in human neuroscience, 8, 371.

[117] González, A., Hayashibe, M., Bonnet, V., & Fraisse, P. (2014). Whole body center of mass estimation with portable sensors: Using the statically equivalent serial chain and a kinect. Sensors, 14(9), 16955-16971.

APPENDICES

Appendix A

Lower limb joints

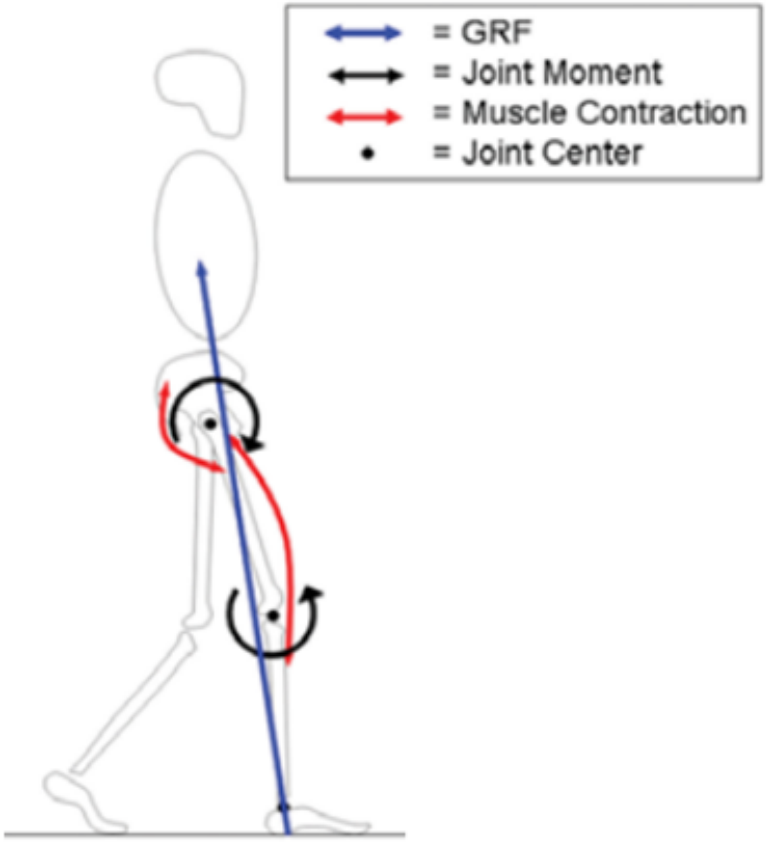


Figure A.1: Motion of hip and knee joint according to muscles contraction[23].

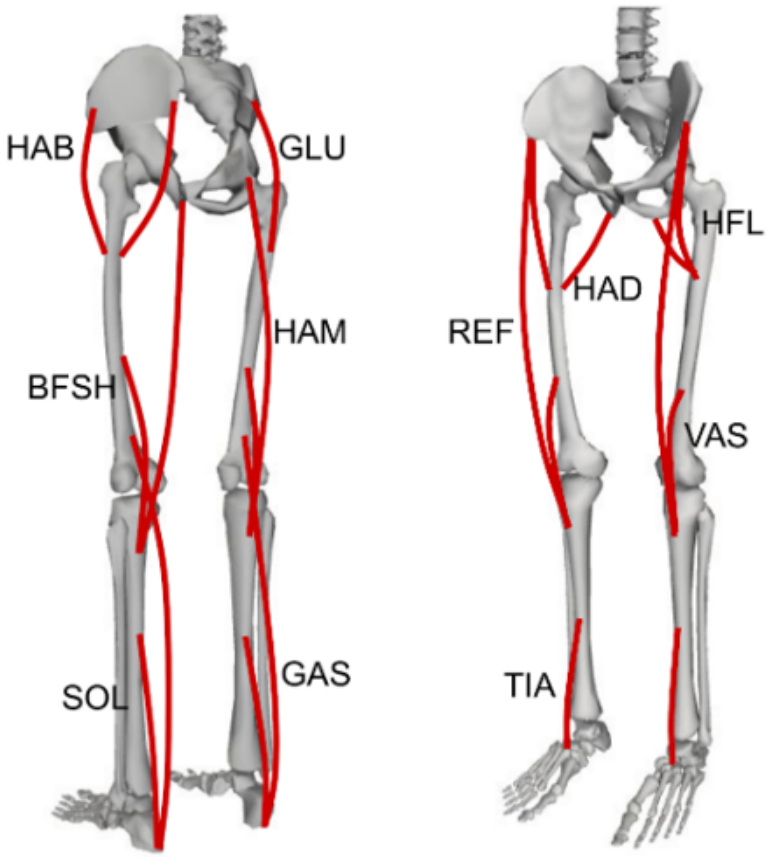


Figure A.2: Prominent muscles for lower limb joints. The muscle groups are hip abductors (HAB), hip adductors (HAD), hip flexors (HFL), glutei (GLU), hamstrings (HAM), rectus femoris (REF), vastus (VAS), biceps femoris short head (BFSH), gastrocnemius (GAS), soleus (SOL), and tibialis anterior (TIA). [17].

Appendix B

Gait cycle tasks

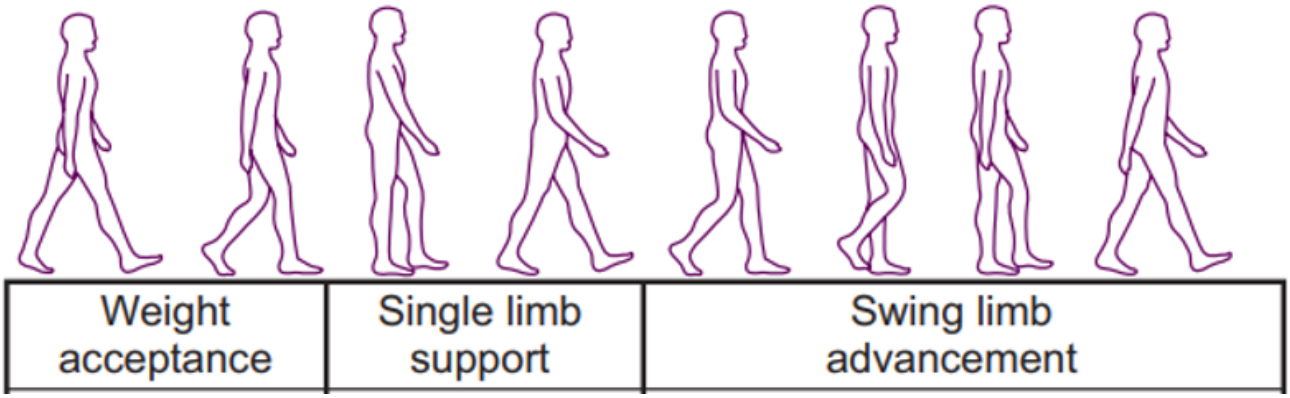


Figure B.1: Gait cycle tasks [22].

Appendix C

Lower limb assistive controllers' classification

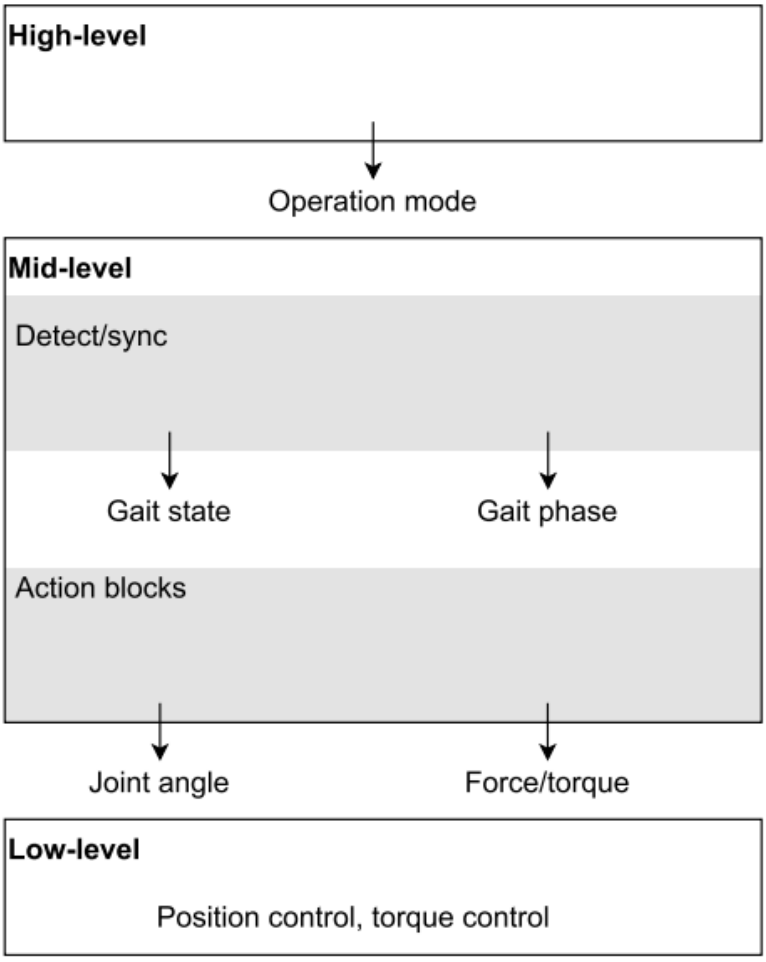


Figure C.1: Simplified diagram [78].

Appendix D

Sensitivity to the neural delay

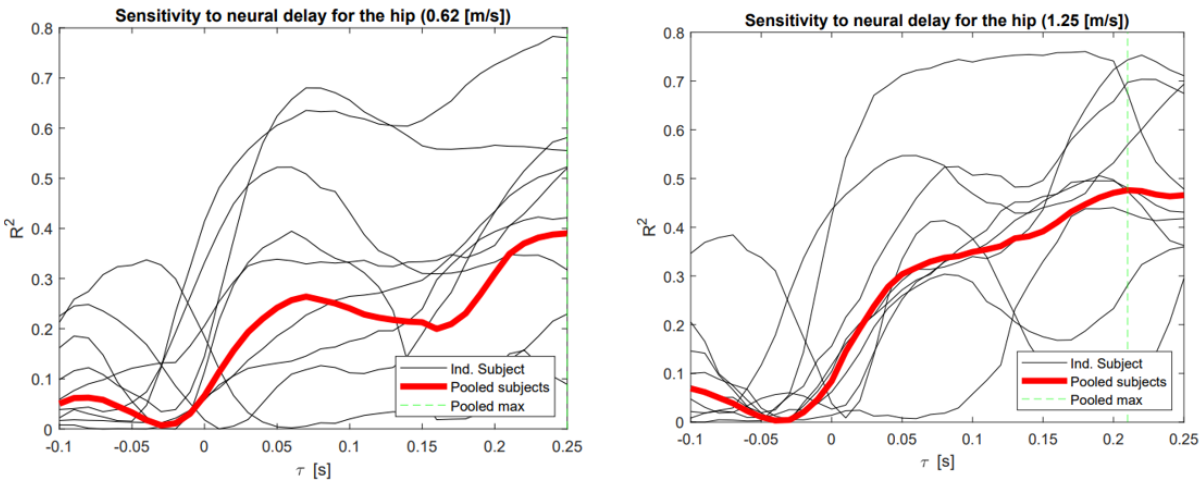


Figure D.1: Sensitivity the COM feedback model for the hip, where the green dotted line represents the maximum of the pooled data (red) and the black lines is the data for each subjects.

Appendix E

Visual representation of models fits at discrete time instance

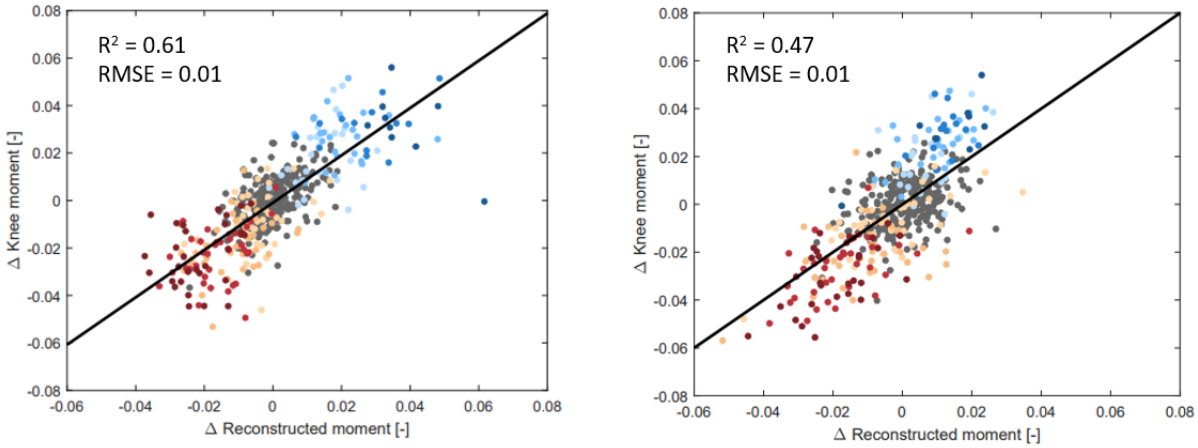


Figure E.1: Reactive knee moments as a function of the reconstructed moment by the COM model (left) and by the local joint model (right) - gray dots represent the unperturbed walking, the red dots the forward perturbation and the blue dots the backward perturbation.

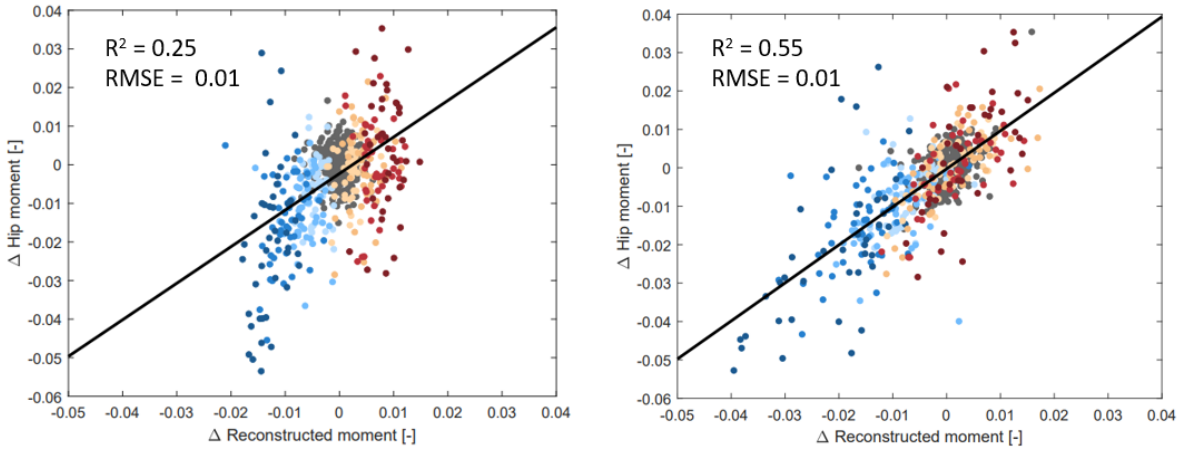


Figure E.2: Reactive hip moments as a function of reconstructed moments by the COM model (left) and by the local joint model (right) - gray dots represent the unperturbed walking, the red dots the forward perturbation and the blue dots the backward perturbation.

Appendix F

Added blocs to Geyer's bipedal locomotion model

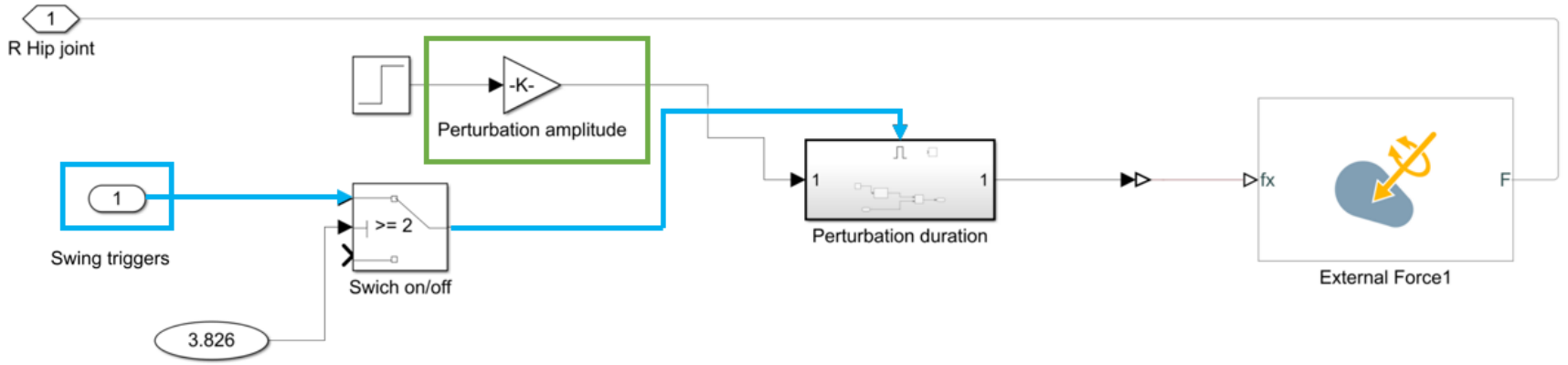


Figure F.1: Perturbation bloc with the perturbation amplitude represented in the green square and the neural swing trigger in the blue square.

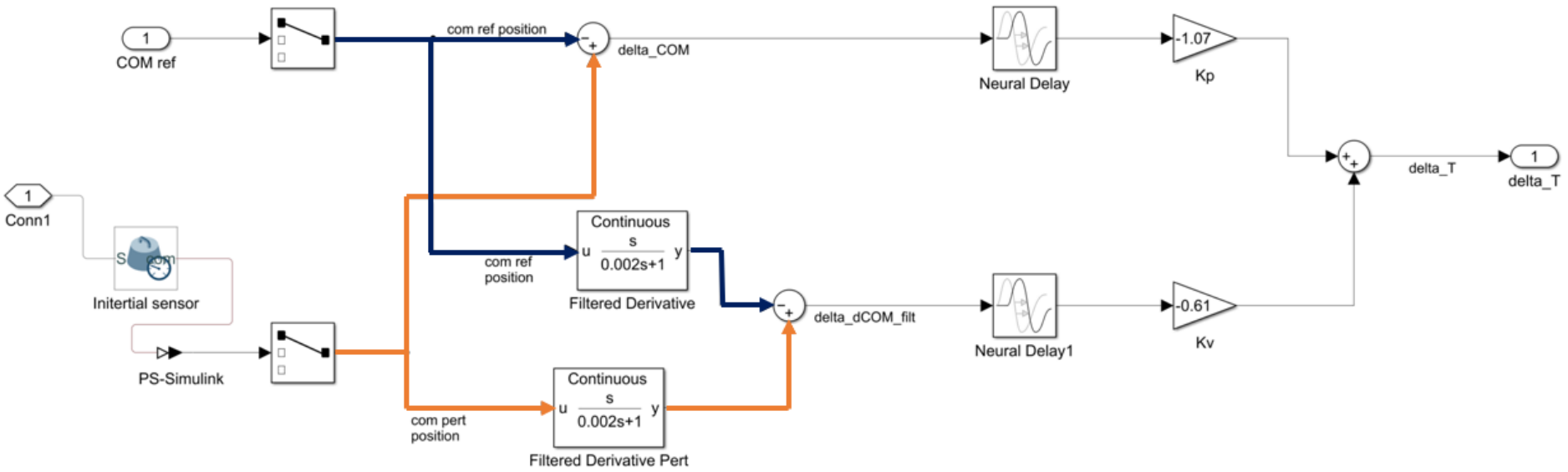


Figure F.2: Controller bloc where the orange path represents the perturbed center of mass and the blue path the reference COM. At left, we can see the inertial sensors which senses the center of mass of the virtual human.

Appendix G

Comparison between model, experimental and our data outputs

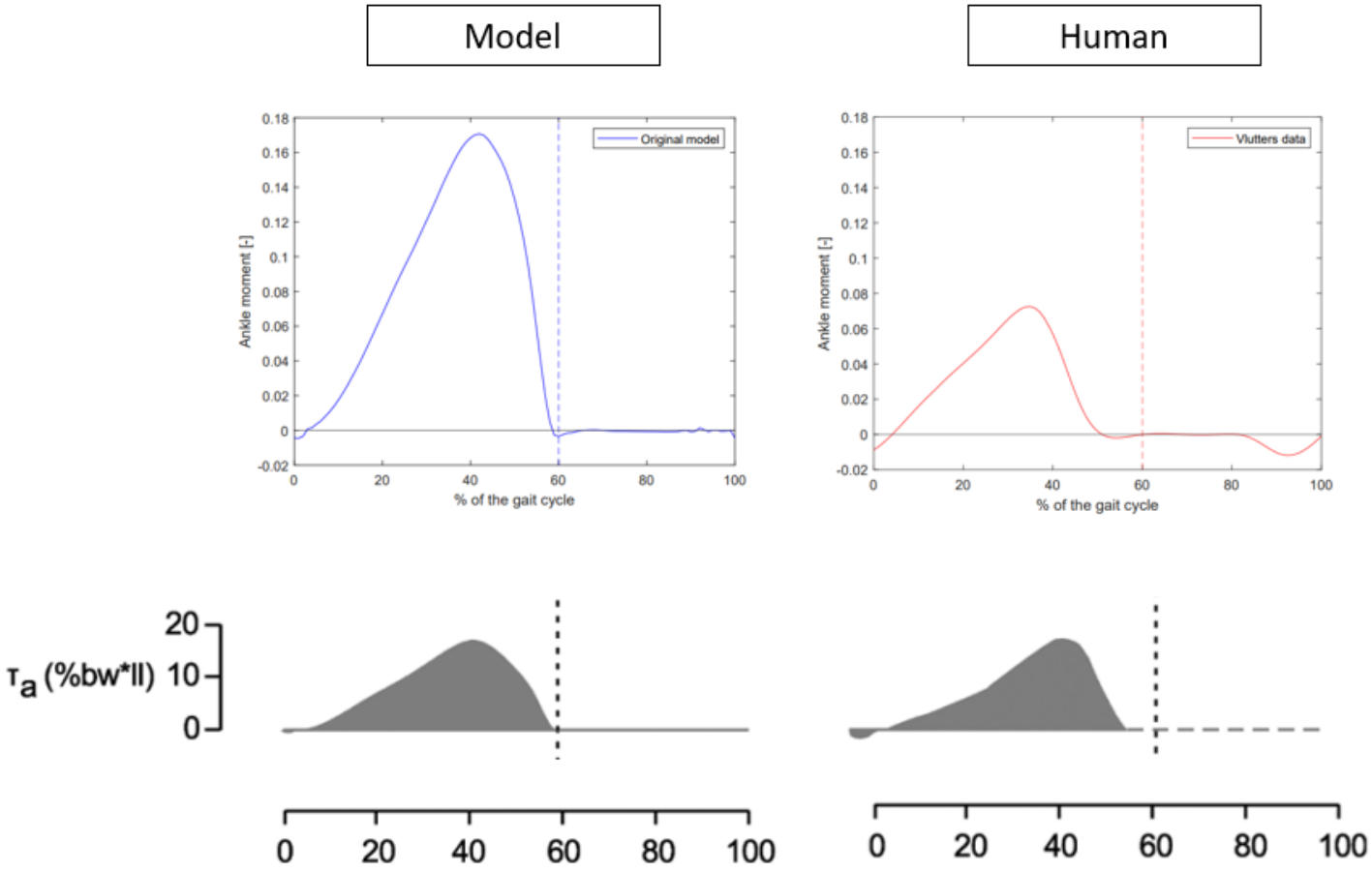


Figure G.1: At the right side of the chart, the torques for the ankle have a maximum plantarflexion of 0.16 for our results (blue) and the ones from the article (bottom left). The conventions are different than the ones used in the thesis. At the left side of the chart, we represented Vlutters experimental data (red) output and the human set with which Geyer's compared his model (bottom right). The dotted lines represent the separation between swing and stance phase.

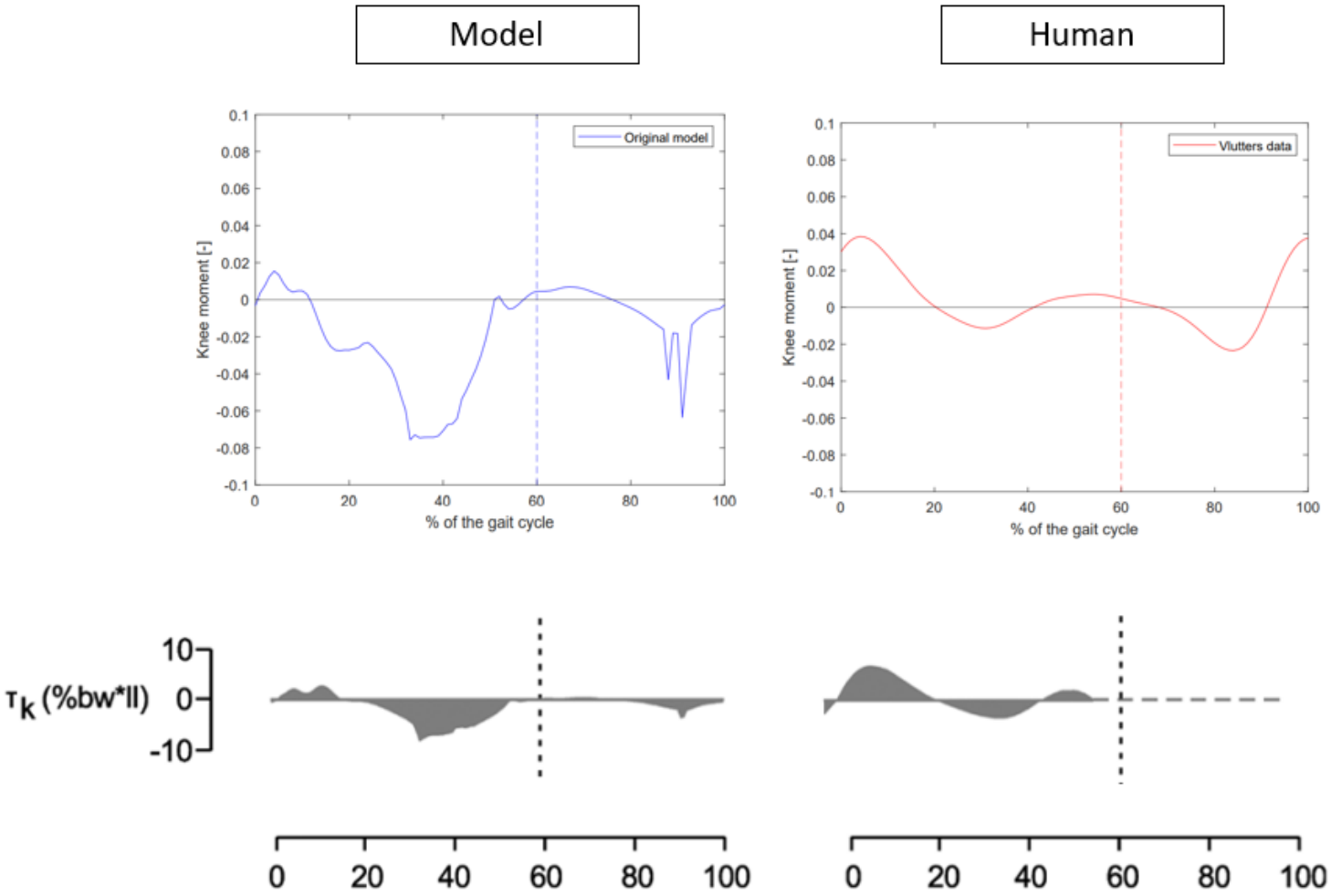


Figure G.2: At the right side of the chart, we can see quasi similar shape behaviors between our results (blue) and the ones from the article (bottom left) for the knee joint. At the left side of the chart, we represented Vlutters experimental data (red) output and the human set with which Geyer's compared his model (bottom right). The dotted lines represent the separation between swing and stance phase.

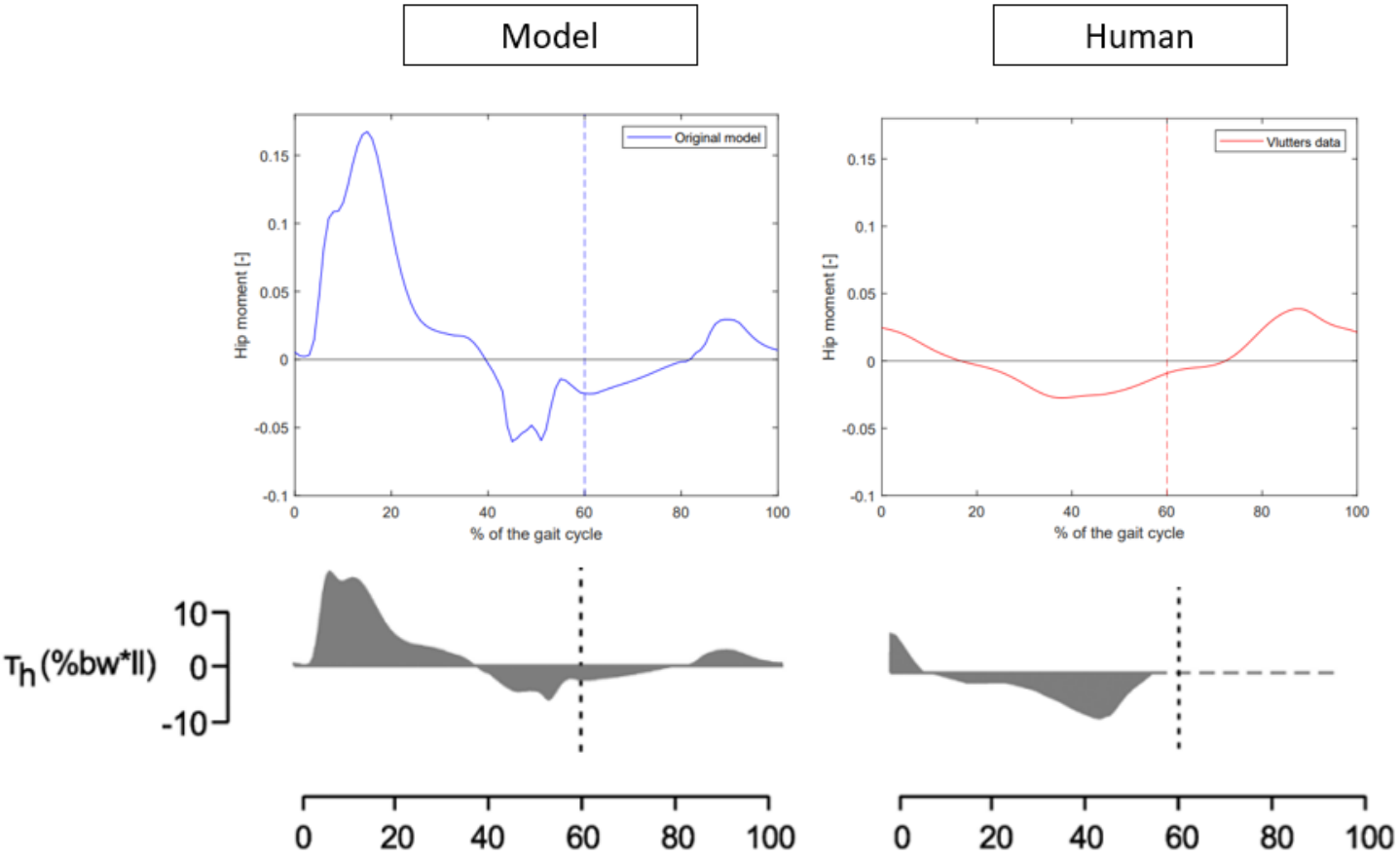


Figure G.3: At the right side of the chart, we can see quasi similar shape behaviors between our results (blue) and the ones from the article (bottom left) for the hip joint. At the left side of the chart, we represented Vlutters experimental data (red) output and the human set with which Geyer's compared his model (bottom right). The dotted lines represent the separation between swing and stance phase.

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