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SIMULATION AND ANALYSIS OF A PROSTHETIC ANKLE USING THE TACIT LEARNING SYSTEM CONTROL ALGORITHM

Examiners: Prof. Heikki Handroos
Dr. Ming Li
Dr. Shingo Shimoda

ABSTRACT

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The objective of this thesis is to apply the Tacit Learning System (TLS) developed by Shimoda et al. to a prosthetic lower limb. The ankle prosthesis is constructed in simulation while three different control schemes, all based on TLS, are applied and analyzed. During this thesis, two experiments are conducted to provide additional data helping with understanding and guiding as input for the simulated prosthesis. From the three control schemes, optimizing the stiffness with TLS indicates have the best and most stable effect on the prosthesis. Therefore, it is concluded that the Tacit Learning System has potential to be applied to an actual ankle prosthesis.

ACKNOWLEDGEMENTS

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CONTENTS

1 LIST OF SYMBOLS AND ABBREVIATIONS

ω	Angular Velocity
ASIS	Anterior Superior Iliac Spine
B.W.	Body Weight
CBS	Center for Brain Science
deg	Degrees
EMG	Electromyography
GRF	Ground Reaction Force
N	Newton
N.O.	Natural Order (cluster)
P	Power
T	Torque
TLS	Tacit Learning System
VTN	Variable Threshold Neuron

2 INTRODUCTION

Transtibial amputees use about 20% more energy to maintain the same walking gait as non-amputees (Molen 1973). Because a passive prosthesis, or the limited amount of active prostheses on the market, are not able to exert the same amount of torque as a human ankle at the right timing of the walking gait. With an active prosthesis, the problem mainly lies in the control algorithm, rather than the available hardware technologies (Kim et al. 2015; Herr et al. 2011).

The Tacit Learning System (TLS), developed by Shimoda et al. (2008) at *RIKEN Center for Brain Science* (1997), is a control algorithm based on compound control. It tries to mimic the neurons in the brain mathematically in order to create an intuition for the robot. The TLS has been proven to work with a bipedal humanoid robot (Shimoda et al. 2009) as well as a hand prosthesis (Oyama et al. 2016). The main difference between TLS and ordinary control algorithms is that TLS tries to understand and learn how to work with the human rather than the human trying to learn how to understand and work with the robot.

Therefore, this idea of creating an intuition for a robot will be expanded to a prosthetic ankle.

2.1 Objectives

The objective of this research is to create a working model of an ankle prosthesis, controlled by the tacit learning system. This will be done using a simulation of the prosthesis to prove the concept. The following research questions will be answered:

- How can an ankle prosthesis best be modeled in a non-complex way while still being a good resemblance of an actual prosthesis?
- What optimization parameters should be used in the Tacit Learning System for an accurate optimization?
- What are correct criteria to define if the Tacit Learning System works accurately for an ankle prosthesis?

The hypothesis is that the tacit learning system used with an ankle prosthesis can significantly improve the human metabolism during the walking gait. The objective of the research just like the aforementioned research questions will be answered in this thesis.

2.2 Thesis organization

This thesis follows the IMRAD structure. After the introduction and background information, the methods are described. Then, the results and analysis are presented. This is followed by a discussion and final conclusions of the thesis, as well as a suggestions for future work.

The thesis is conducted for the most part in Nagoya, Japan, at RIKEN Center for Brain Science in the Intelligent Behaviour Control Unit. Dr. Shingo Shimoda is supervising the master's thesis during the stay at RIKEN CBS.

3 LITERATURE STUDY

In this section, several background aspects which are necessary to understand the thesis are introduced. First, the focus is on transtibial amputees, followed by a section about the current state of the art of ankle prostheses and their control systems. Next, the human gait is analyzed and the concept of tacit learning is explained.

3.1 Transtibial amputees

Transtibial amputation, or below-knee amputation, is one of the more common amputations (see figure 1). About 60-70% of transtibial amputations are due to a disease with blood circulation in the lower limb resulting in the need for surgical removal. During this surgery, the surgeon tries to shape the stump in such a way that it can be used with a prosthetic leg. The most important part missing in this area is the ankle and the foot, which are made up of many small bones working smoothly together.

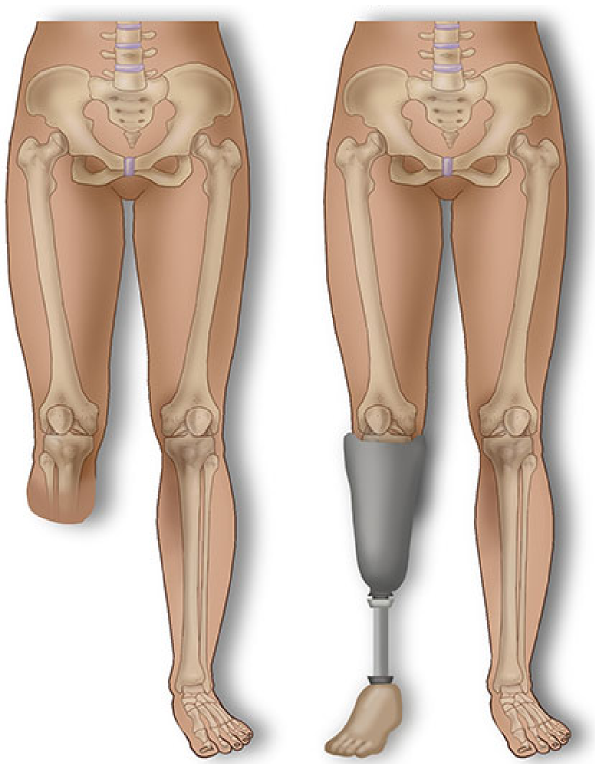

Figure 1: Transtibial amputee without and with prosthesis (Move Forward 2018)

One of the main functions of the ankle and foot is shock absorption. By any kind of gait movement, the foot is the part that touches the ground and adsorbs the energy. The foot is also used for stability; on uneven grounds for example, the foot is able to walk steadily without any problems. This is referred to as proprioception, the haptic feedback of telling the foot's position and interaction with the ground, as well as the texture, slope, etc.

Current prosthetic feet are either designed to have a good feeling and be accommodating or are firm and usually made of a leaf spring. However, to combine these two factors still remains a challenge nowadays. Ideally, the prosthetic ankle is soft and adsorbent during the heel strike but gives a push during the toe-off.

3.2 Current state of the art

There are several prosthetic ankles on the market aimed for transtibial amputees. All these prostheses are designed to restore (a part of) the human ankle's function. These can be split up in three different categories (Versluys et al. 2009). The first category being the first ones on the market, referred to as conventional feet. These do not have any motion and are only designed to look like human feet. The second category, which is already more interesting to analyse, is the energy storage and return (ESR) feet. These usually consist of a (leaf) spring but do not have any active elements. However, none of the ESR prostheses can significantly improve the human metabolism or enhance the gait since the energy stored and returned is only a fraction of what a real ankle produces (Nielsen et al. 1988).

Since about 10 years the first so-called bionic foot came out on the market creating the third category. These have an active control system including stabilization and propulsive functions (Cherelle et al. 2014). Since this is the most advanced category and the designed prosthesis in this thesis will fall into this category, these control systems (Jimenez-Fabian et al. 2012) will be evaluated in this section.

The most commonly used control systems nowadays are gait pattern generators, hierarchical control systems, motion intent recognition, which will be explained in the following section.

3.2.1 Gait-pattern generators

The gait-pattern generator control scheme highly depend on the fact that the walking motion is periodical. Pre-programmed patterns that may be adjusted depending on the stride time are used to mimic ankle behaviour. A schematic block diagram is shown in figure 2.

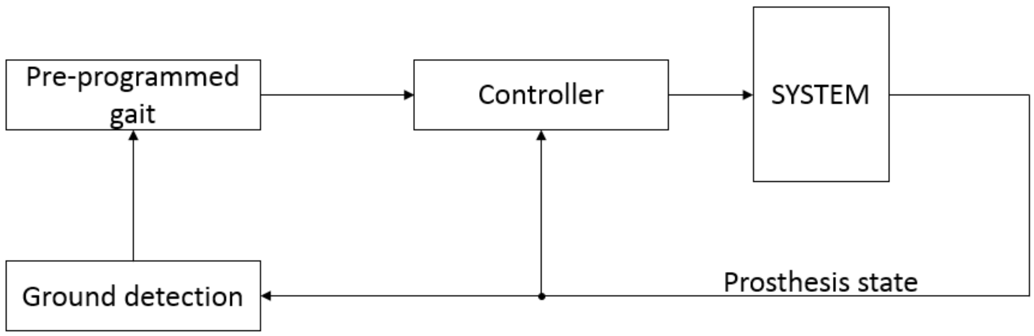

Figure 2: Block diagram of a typical gait-pattern generator

An example is the SPARKy designed by Arizona State University in Arizona, USA (Hitt et al. (2007), Bellman et al. (2008)), shown in figure 3. The prosthesis is guided by a reference gait pattern that is used to control the actuator position. The detection of the heel strike is used to define the start of the stride.

Although this approach works relatively well for some patients, the walking gait of a human differs too much from person to person to use one correct pre-programmed gait that works for everyone. There does not exist a 'one-size-fits-all' gait.

Another research project by Holgate et al. (2008) uses the same principle. The tibia angle and angular velocity are used to fit a predefined mathematical function with respect to the gait percentage. An additional method is used to adjust the motion of the actuator in duration and amplitude to compensate for the differences in walking speed, based on Fourier coefficients. Despite the differences in humans, this method has proven to be effective (Holgate et al. 2009).

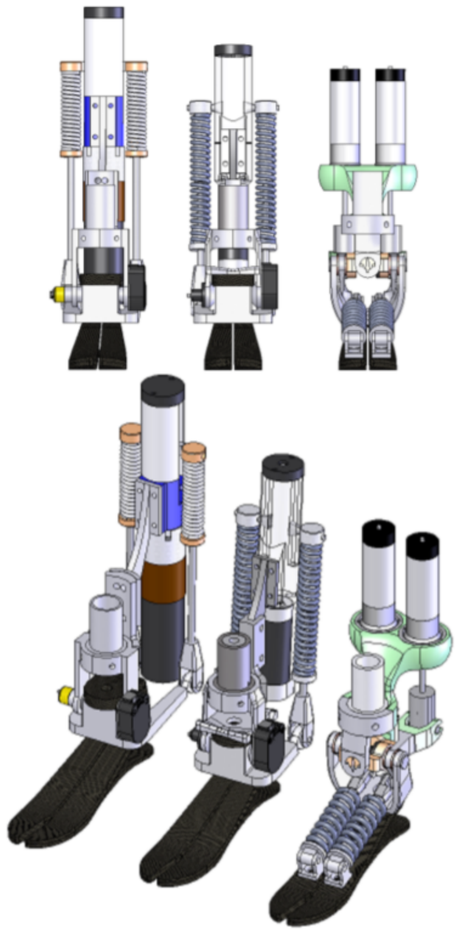

Figure 3: The three versions of SPARKy (Bellman et al. 2008), left the initial design and right the current improved design

3.2.2 Hierarchical control systems

The ankle behaviour can be described as a combination of the passive elements, stiffness and damping, and the active power source, during the stance phase. During the swing phase, the ankle resets itself and prepares the foot for the next stance phase. Therefore, many control algorithms base their stiffness and damping factors as a function of the gait phase, speed and other criteria.

This way of controlling the prosthetic ankle can be seen as hierarchical control: first, a control algorithm is used to define the current phase within the gait. Then a different type of controller is used each of these phases. A schematic overview can be seen in figure 4.

An example of hierarchical control is by Blaya et al. (Blaya 2002; Blaya et al. 2004). They designed an active ankle-foot orthosis mainly for patients with drop foot. The angle between the shank and the foot is measured using a potentiometer and the ground reaction forces are measured using capacitive force plates, and a linear motor is used to actuate the orthosis.

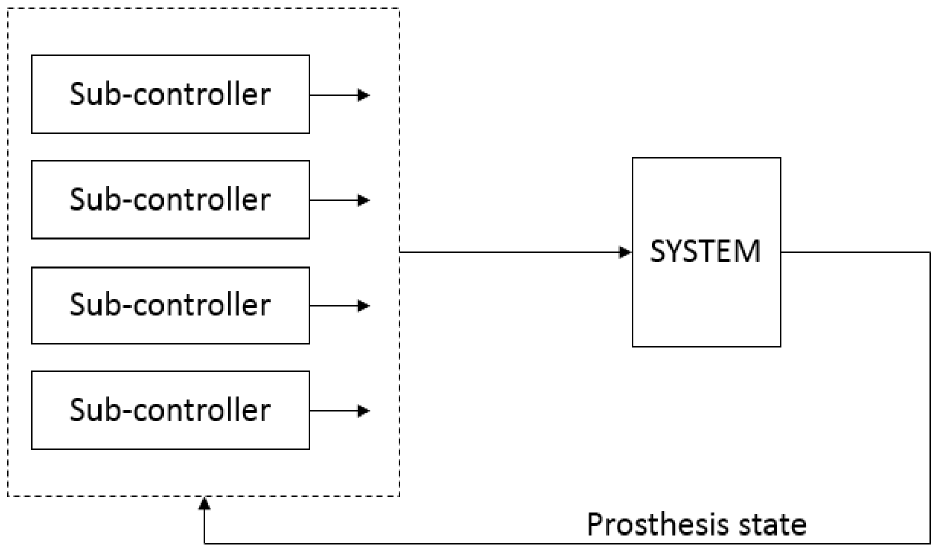

Figure 4: Block diagram of a typical hierarchical control system

3.2.3 Motion intent recognition

One of the most challenging aspects of the control algorithms that still requires further research is efficient algorithms to determine motion intention by the user. Several research groups have been developing these algorithms.

Ferris et al. (2005) have developed powered ankle orthoses by using artificial pneumatic muscles. Again, the main problem does not lie in the mechanical and hardware capabilities available, but on the controls. A signal proportional to the muscle activation pattern is used to determine the motion intention of the user. The EMG (electromyography) signals are processed in real-time to control the pneumatic muscles. A schematic overview of this control algorithm can be found in figure 5.

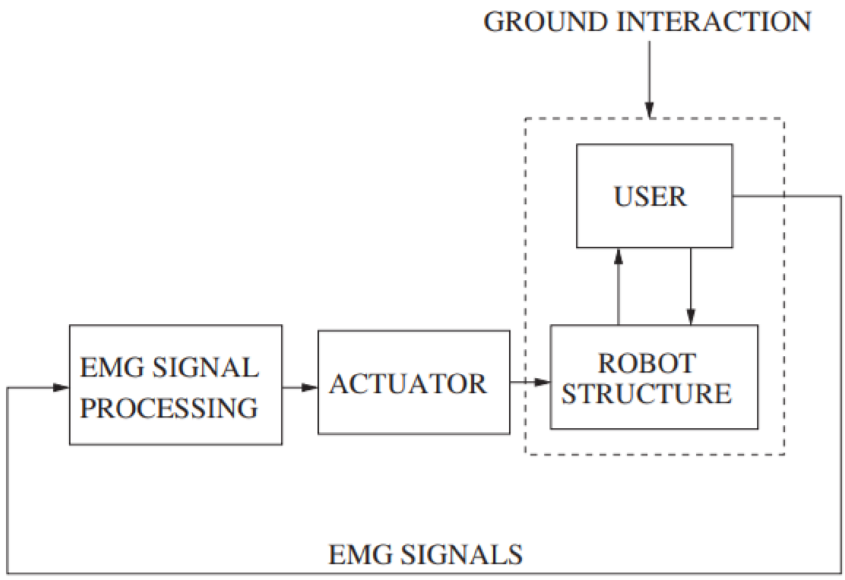

Figure 5: Block diagram of the motion intent recognition algorithm by Ferris et al. (2006)

3.2.4 Other control schemes

A fine-state machine for a knee-ankle prosthesis has been introduced by Sup et al. (2008) with variable stiffness and damping parameters. It can take four different values depending on four phases of the walking gait: stance flexion/extension, pre-swing, swing flexion and swing extension. Switching between these states is determined by threshold values for the ankle angle, ankle torque, knee velocity and body weight force.

Another relatively simple design is developed by Sawicki et al. (2006), using hand-held push buttons to control the artificial muscles with pneumatic plungers. However, this control scheme requires a lot of attention from the user.

3.3 Human gait

The human gait is well-analyzed these days but still is a complex phenomenon. In this section, first a general description of the walking gait is presented. This is followed by the important joints for the walking gait which will be analyzed further. The kinematics is described followed by the kinetics to create these motions. Last, the muscle activity is explained.

3.3.1 Walking analysis

The walking gait throughout this thesis is defined as one stride of walking starting at the moment the heel touches the ground and finishes at this exact point as well. Analyzing just one foot, there are two main phases: the stance phase, where the foot is touching the ground, and the swing phase. A schematic overview is given in figure 6.

The stance phase can again be split up in three sub-phases: the first one starting at the heel strike until the foot is flat, which is usually the shortest of the three phases and referred to as controlled plantar flexion. The second sub-phase starts when the foot is flat on the ground up until the ankle reaches its maximum angle, referred to as the controlled dorsiflexion. In these two sub-phases, energy is stored into the ankle. In the third phase, powered plantar flexion, the toes push off and an impulse is given for continuing the walking motion. This sub-phase ends when the foot leaves the ground. (Palmer 2002)

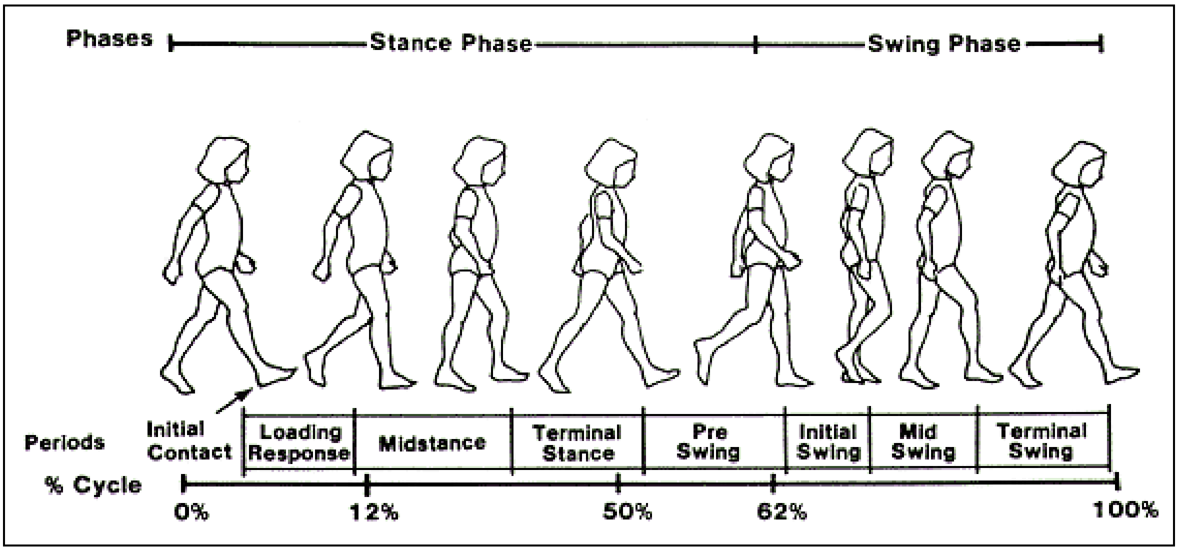

Figure 6: Representation of the gait cycle

3.3.2 Joints

Three joints in each leg contain the most important degrees of freedom for walking: the hip, knee and ankle joint. The ankle joint will be replaced by a prosthesis so it is important to fully understand the functions of this joint.

The ankle joint can be described as a hinge joint, since its main direction of freedom is a rotation around the y-axis. This ankle angular motion can be split up into two flexion motions: dorsiflexion and plantar flexion. In dorsiflexion, the ankle angle is moving towards the leg in the upward direction, while plantar flexion is the movement in opposite direction. next to this, eversion and inversion, around the x-axis, is possible for stabilizing the ankle (Brockett et al. 2016). The range of motion varies significantly between individuals, but on average a human has 10-20 degrees of dorsiflexion to 40-55 plantar flexion, and 23 degrees inversion to 12 degrees eversion. (Grimston et al. 1993).

The ankle has a high load-bearing area which results into lower stresses on the hip and knee. The ankle has a variable stiffness and damping depending on the walking speed and several other variables like the ankle angle.

3.3.3 Kinematics

Kinematics describes the positions and angles of the joints without looking at external forces. Since the gait is a repetitive moment, one gait cycle, or stride, will be used to describe the kinematics. These days kinematics can be easily extracted during experiments with motion capture cameras. It is important to note that many (muscle) forces are involved to create the stride which are not considered here.

For this kinematics analysis, the software OpenSim (*Stanford University* 2010) is used. In figure 7, the positions of the knee, ankle and toes are shown. The walking speed is 1.25 m/s (4.5 km/h) and the start and end position are the same, simulated like walking on a treadmill. The data comes from an initialized OpenSim model of a male subject with a length of 1.80 meters and weight of 75 kilograms. This data is also used for further analysis and the initial design of the algorithm.

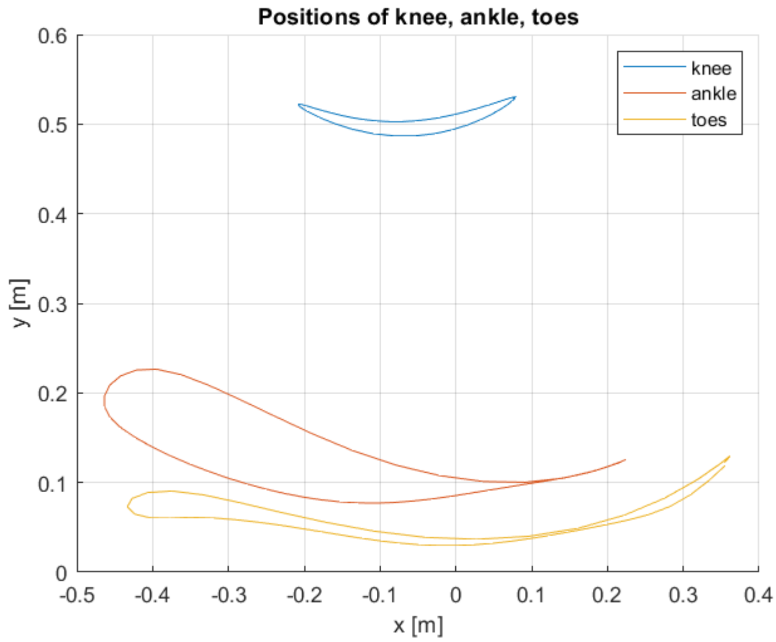

Figure 7: Positions of the knee, ankle, toes

In figure 8, the angles of the hip, knee and ankle are shown. All angles are 0 degrees in rest-standing mode. The hip angle is relative to the vertical axis of the ground, the knee is relative to the hip angle and the ankle angle is relative to the knee angle. An overview can be seen in figure 9, the initial stance of the walking gait used in figures 7 and 8. The hip angle is positive whereas the knee and ankle angles are negative.

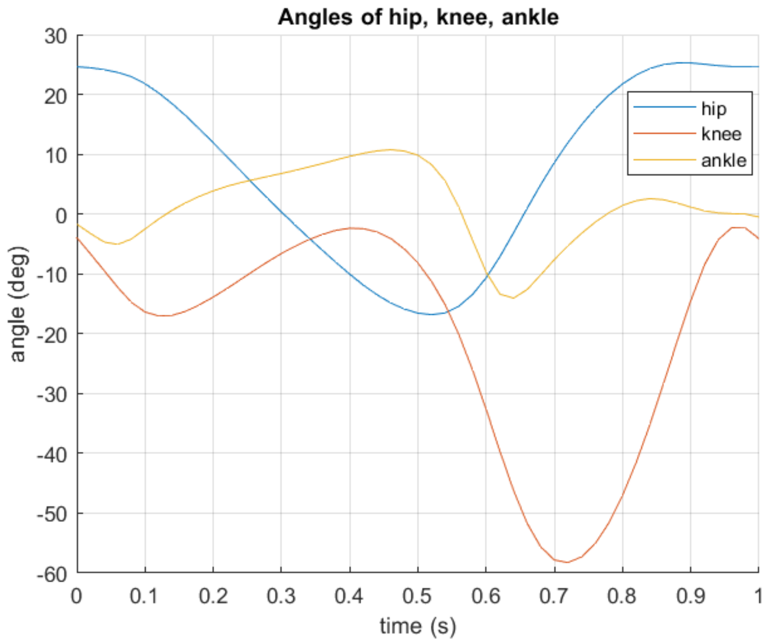

Figure 8: Angles of the hip, knee, ankle

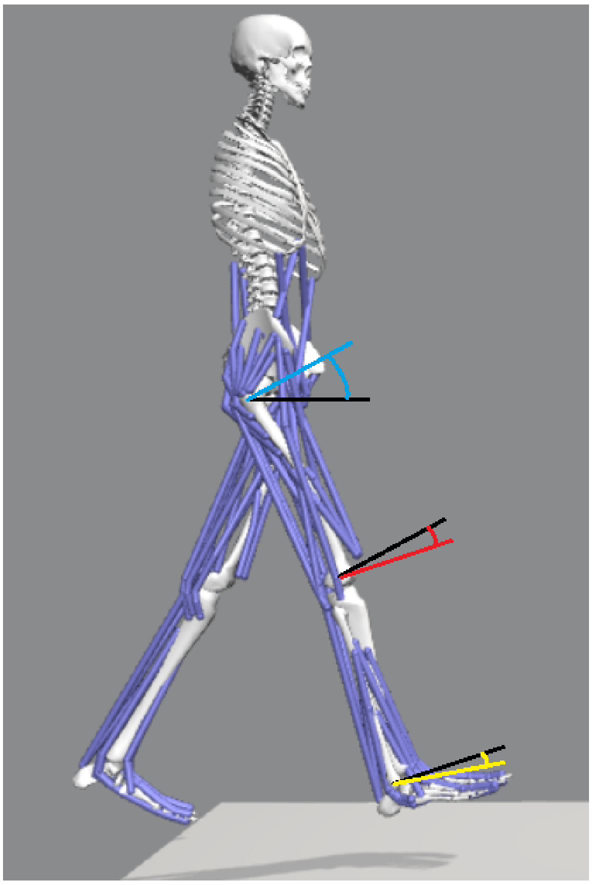

Figure 9: OpenSim initial stance with angle descriptions

3.3.4 Kinetics

Kinetics describes the forces used to guide a motion. To create the kinematic motions, an important factor to analyse is the forces and torques applied to the human body during the walking gait. This can be split up into two categories: the external forces, like ground reaction forces, and internal forces and moments in the joints itself Winter (1987).

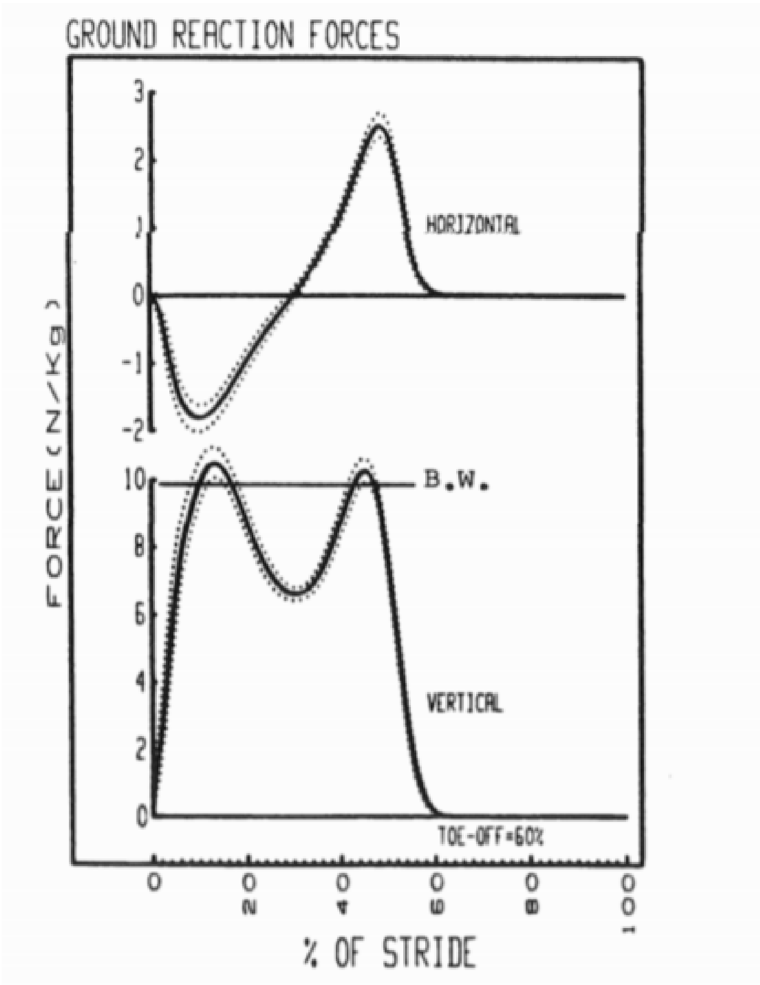

Figure 10: Ground reaction forces (Winter 1987)

The ground reaction forces (GRF) are describing the net vertical and shear forces on the sole of the foot induced by the ground. Figure 10 shows the average horizontal an vertical ground reaction forces normalized to Newton per kilogram. The horizontal GRF first has a negative peak indicating the slowing down (negative acceleration) of the body, and a positive peak in the second half representing the body is accelerating again.

The B.W. in the vertical ground reaction forces represent the body weight. The shape is typical as seen in literature, with the first peak representing the weight put onto the ground and the second peak representing the push off by the toes.

The moments relative to body mass are estimated and shown in figure 11. The net moments are calculated according to Winter (1987). The support is closely related to the ground reaction force in figure 10. The ankle torque is most interesting here, since during the first 40% the angle is in dorsiflexion and thus absorbing energy while during 40% and 60% in plantar flexion, meaning exerting a torque for the toe push off. However, this is not visible in this graph and only known when compared to the ankle angle.

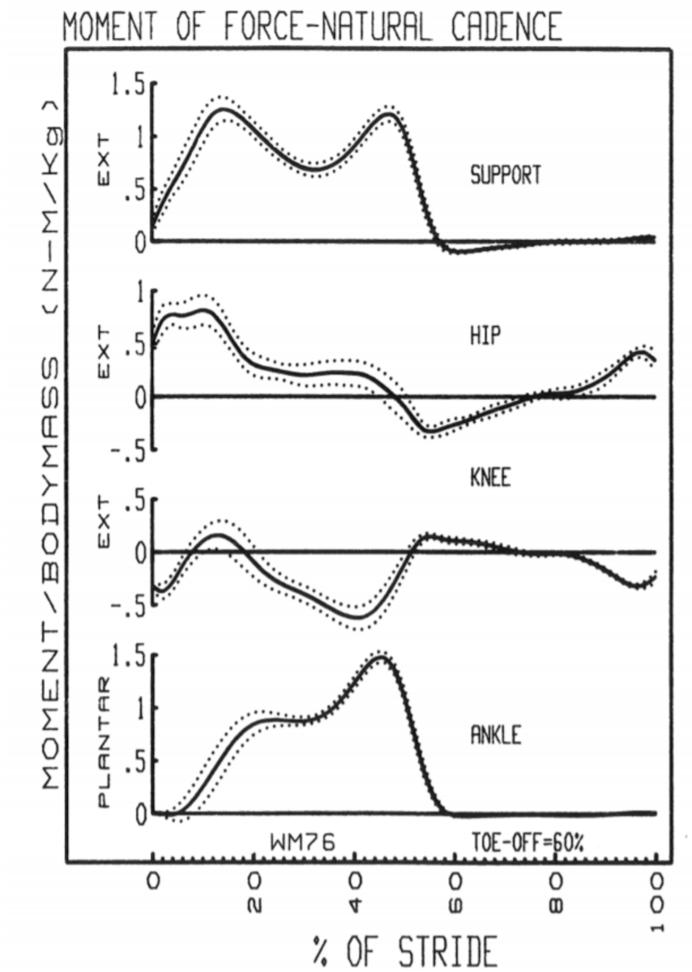

Figure 11: Moments relative to body mass (Winter 1987)

To understand better what is going on within the joints, it is necessary to find another way to represent these variables. In order to distinguish between moment generation and absorption, the power can be analysed. The power, P [W] is the product of the joint torque, T [Nm] and angular velocity, ω [rad/s], as described in the following equation:

$$P = T * \omega \tag{1}$$

If both the torque and angular velocity are in the same direction, the power is positive and thus generating energy. If the variables have an opposite polarity, the power is negative and energy is absorbed. An overview of the angle is shown in figure 12. In the power graph, in part one energy is absorbed and in part two energy is generated.

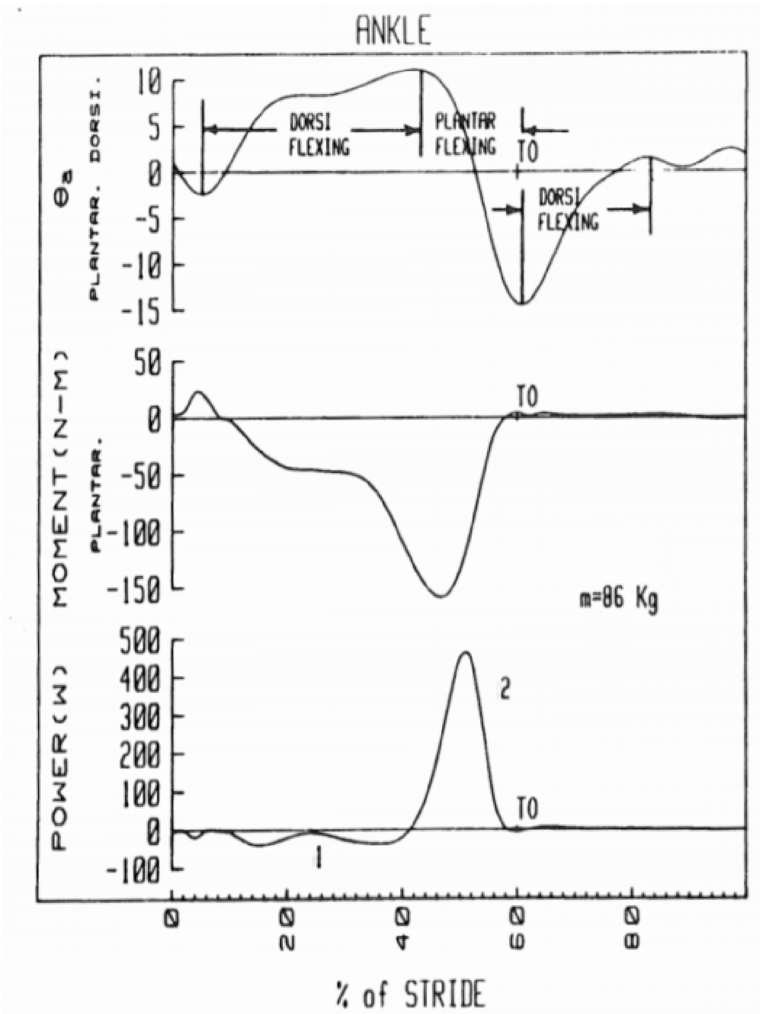

Figure 12: Ankle angle, moment and power (Winter 1987)

3.3.5 Muscle activity

The next step is to analyse where these generated torques come from. The human anatomy of a leg knows many muscles out of which some are more important during the walking gait than others. Since there are about 40 important muscles per leg, only the ankle flexion will be described.

Dorsiflexion is controlled by four muscles: extensor digitorum longus, extensor hallucis longus, peroneus tertius and tibialis anterior. The location of these muscles can be seen in figure 13. The peroneus tertius contribues the least torque whereas the tibialis anterior the most.

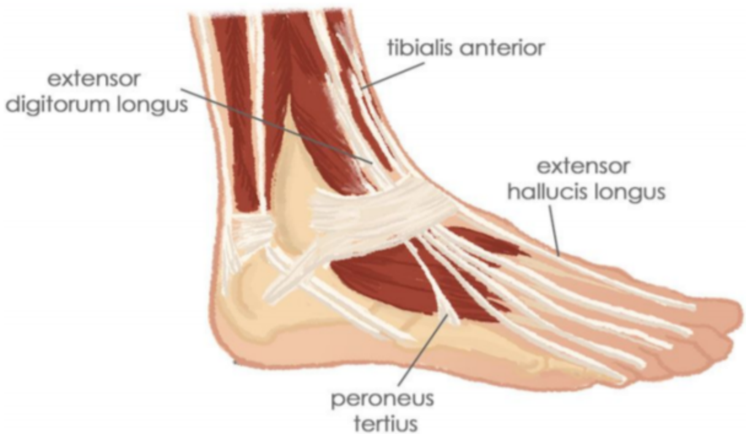

Figure 13: Ankle muscles used for dorsiflexion (Al-Makarem 2017)

For the plantar flexion movement, seven muscles are used: flexor digitorum longus, flexor hallucis longus, gastrocnemius, peroneus brevis, peroneus longus, soleus, tibialis posterior.

The biggest and most important is the gastrocnemius, which is a big part of your calf muscle. Just as the soleus, these two muscles are most important in plantar flexion. The peroneus longus and perneus brevis are both used for stability while in plantar flexion.

3.4 Tacit Learning System

The Tacit Learning System (TLS), designed by Shimoda et al. (2008), is used to control more complex behaviours in an environment with multiple disturbances and unpredictable situations. The TLS is based on compound control, aiming to mimic the neural control we have in our brains. Without knowing all the details of the dynamics and a self-adapting algorithm it is possible to create an intuition to operate in new situations.

3.4.1 McCulloch-Pitts neural model

The TLS is based on a classical neural model designed by McCullough et al. (1943). In this model, a few assumptions are made. The most important assumption is that the neuron activity of an individual neuron can be expressed by a boolean value, it is either fired (1) or in rest (0).

The system can be divided into two parts. One part takes care of the input of the system and the other part makes a decision based on that input. This can be easily demonstrated with a simplified example:

Imagine I am deciding if I should go on a holiday or not. The answer is a boolean value, either I go or I do not go. If I am going depends on certain input factors:

- u_1: Time & money
- u_2: Mountains
- u_3: Festival
- u_4: Friends

The inputs could be divided up into two categories: excitatory and inhibitory. The inhibitory inputs have a bigger effect on the decision making, independent of other inputs. For example, take input u_1, if I cannot take days off from work or I don't have sufficient funds to go, the output will always be 0.

The other inputs are excitatory inputs and can be combined together. If there are mountains or a music festival in my preferred genre at the holiday destination, I am more inclined to go,

but it is not a must for a holiday. The same holds for if my friends are joining me, it would be a positive influence but I also don't mind to travel alone. If two out of three of the excitatory inputs are true, then I will go on a holiday.
In mathematical terms:

$$s(u_1, u_2, u_3, ...u_n) = s(\mathbf{u}) = \sum_{i=1}^{n} u_i \tag{2}$$

$$\begin{aligned} N = f(s(\mathbf{u})) &= 1 \quad if \quad s(\mathbf{u}) \geq \theta \\ &= 0 \quad if \quad s(\mathbf{u}) < \theta \end{aligned} \tag{3}$$

Where θ represents the threshold parameter. Meaning in this case, θ is three (u_1 has to be true and two out of three of u_2, u_3, u_4 has to be true). Thus, the neuron N can either be 1 (going on holiday) or 0 (staying home) depending on the inputs.

3.4.2 Variable Threshold Neurons

Variable Threshold Neurons, or VTNs, are based on the neurons described in the previous section. However, this time, the threshold is not a fixed value but it can change over time. The idea is that if the neuron is fired at time t, the threshold is raised by $\overline{\Delta\theta}$. However, if at time t the neuron is not fired, the threshold is decreased at $\underline{\Delta\theta}$. This is done to increase and decrease the chance of firing at time $t+1$ respectively. Mathematically, this can be described as:

$$\theta(t+1) - \theta = \overline{\Delta\theta} N(t) + \underline{\Delta\theta}(N(t) - 1) \tag{4}$$

The variable threshold neuron is described by the combination of equations 2-4. To these VTNs, weight factors are added, referred to as the extended Hebbian rule, discovered by Hebb (1949). According to Hebb, the neuron connections have some plasticity which affects the signal transmission. Imagine neurons N_1 and N_2 are connected, if both are fired at the same time, the weight factor between these two neurons is increased or decreased depending on a third variable, the mediator (M). Mathematically, this can be described as:

$$w(t+1) - w(t) = \overline{\Delta w} N_1(t) N_2(t) M(t) + \underline{\Delta w}(N_1(t) N_2(t) M(t) - 1) \tag{5}$$

If both $\overline{\Delta w}$ and $\underline{\Delta w}$ are positive, it is referred to as potentiation. Whereas if both are negative, it is called inhibition. This additional rule is referred to as the classical Hebbian rule.

3.4.3 Representation

The neurons all function in either the firing or rest state, meaning the most efficient way to represent these are in bits. However, since the actuator values can be decimal values, a cluster of neurons is used to represent numerical values. These values can only be integers since the individual neurons are also integers. This is denoted with the symbol $[u]$. This means that the fractional part of the actual value minus the symbol (u-$[u]$) becomes an error. The threshold of every k^{th} element is set to be k:

$$\theta_k = k \tag{6}$$

Which is referred to as the Natural Order (N.O.) cluster. Mathematically represented, the integer part of the input is shown as:

$$[u] = \sum_{k=1}^{N} \mathbb{1}(u-k) \tag{7}$$

This method can only represent positive values. Therefore, an identical extra network is used for the negative values. The sensor output is transformed into two positive numbers I^P and I^N, such that

$$\begin{aligned} I^P = I_s, \quad I^N = 0 \quad if \quad I_s \geq 0 \\ I^P = 0, \quad I^N = I_s \quad if \quad I_s < 0 \end{aligned} \tag{8}$$

With the output O^P as a result of I^P and O^N from I^N, giving the final output as:

$$O = O^P - O^N \tag{9}$$

The combination of clusters is able to compute to four basic arithmetic operations: addition, subtraction, multiplication and division.

4 METHODS

To answer all research questions, the thesis is split up into two main sections: an experimental part and a simulation part. The most important is the simulation, which is necessary to prove the working mechanism of the tacit learning. Two experiments are conducted to help understand the simulation better and to create inputs to test and run the simulation.

It is chosen for a simulation study since it is currently impractical to reach the desired output by experiments. The main reason for this is investing substantial time and money to design and build an ankle prosthesis. Furthermore, due to the ethical regulations in Japan, it takes several months to start conducting experiments involving transtibial amputees. Therefore, since the main scope of the research is to show the efficacy of tacit learning, this study will form a baseline after which the control algorithm can be applied to physical prostheses.

4.1 Experiments

During the thesis, two experiments are conducted in the lab. The first experiment focuses on the stance time during the walking gait and works with a capacitive pressure sensor shoe. The second experiment uses a motion capture system to collect data of healthy humans walking on a treadmill.

4.1.1 Experiment 1: Kinetics study

To better understand the kinetics, especially ground reaction forces, the center of pressure is analysed during the walking gait. A studies is conducted with a prototype pressure shoe (seen in figure 14a). This shoe uses four capacitive sensors configured as seen in figure 14b to measure the center of pressure. The first and second sensor are compared to see if the participant is leaning forwards or backwards. The third and fourth sensor are used to compare if the participant is leaning more to the left or right. The participants are asked to walk in a straight line while the data of the shoe is collected through Bluetooth.

The goal of this experiment is to see where the center of pressure is located and changes during a step and what the ratio is between the stance time and swing time. The first hypothesis is that the stance time in percentage during a step is more or less average. The second

(a) Side view of the shoe

(b) Capacitive sensor locations

Figure 14: Capacitive sensor shoes to measure pressure used during experiments

hypothesis for this experiment is that the center of pressure during a stride moves from the back of the foot to the front of the foot.

4.1.2 Experiment 2: Kinematics study

The second experiment is executed to collect data of healthy humans walking. The goal of the experiment is to gather walking patterns at different speeds, which then again can be used as input for the simulation model. Especially the knee position and angle are important during simulation, since these are the main input of the simulation. For a complete image, seven positions on the right leg will be measured, as seen in figure 15.

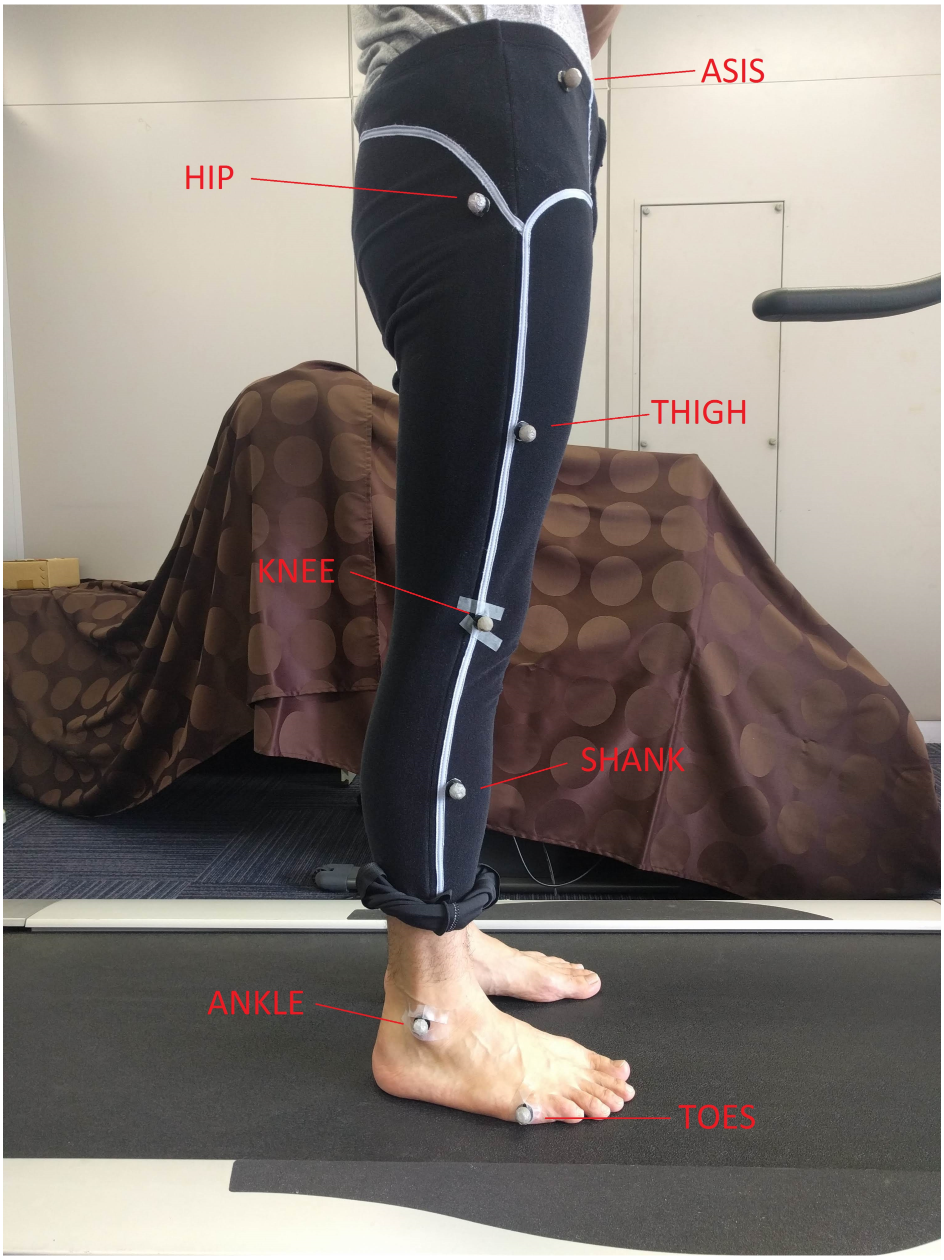

Figure 15: The seven measured positions on the right leg

The participant is requested to walk on the treadmill while three motion capture cameras (Kestrel 2200) are recording. The participant is instructed to start walking at 3.5 km/h, while ten steps of the right leg are recorded. The participant keeps walking and the speed is increased in steps of 0.5 km/h until 5.5 km/h is reached. Creating in total five times a measurement set of ten steps at different walking speeds. The full set-up is shown in figure 16. The Cortex software is used to calibrate, record and post-process the data. Further analysis is conducted using MATLAB.

Figure 16: The complete set-up of the experiment: three motion capture cameras connected to the recording computer, aimed at the treadmill.

4.2 Simulation

The human walking gait is analyzed using Stanford's OpenSim software. Since the goal of the transtibial prosthesis is to create a walking gait as natural as possible, the torques in the hip and knee are estimated from this analysis. This initial data is used for the first tests, before using the actual data from the participants from the second experiment. The simulation is created using MSC ADAMS. The ankle is represented by a torsion spring which connects the foot and the lower leg. The stiffness and damping of the torsion spring are optimized by the tacit learning system, just as the additionally added torque on the ankle joint, forming an active ankle prosthesis. A schematic overview of the MSC ADAMS model is shown in figure 17.

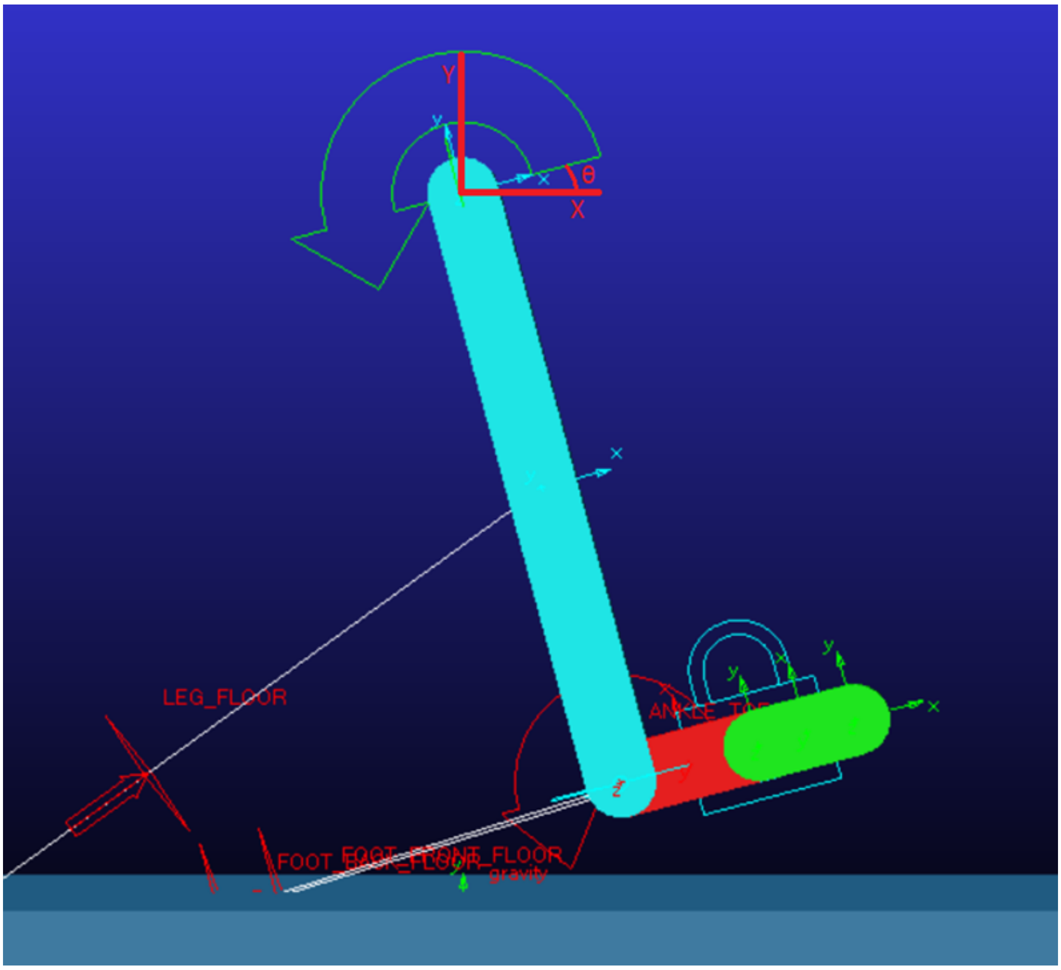

Figure 17: A schematic overview of the MSC ADAMS prosthetic ankle model.

The simulation is guided by kinematics, rather than kinetics. This is done because the kinetics of the walking gait are hard to measure and estimate. The knee motion is chosen as guidance motion in two dimensions with three degrees of freedom: the x-direction, y-direction and angle. The third dimension is left out for simplicity. The knee motion defines the behaviour of the lower leg. The foot and ankle angle are determined by a combination of these induced forces and the ground reaction forces.

The forces measured in the knee are used for the optimization in the Tacit Learning System. It is known that the force working in the Y-direction on the knee is related to the force induced by body weight. In a static situation when someone is standing on one leg, the force induced by body weight on the knee is counteracted with a normal force. This principle will be used in the dynamic situation of walking with a prosthesis.

The goal of the Tacit Learning System is to create a better feeling during walking. This is however hard to prove in simulation, since feeling cannot be measured. Therefore, the forces acting in the knee will be analyzed, just as the change in ankle angle over time. These will both be compared to literature, described in the previous section.

5 RESULTS

In this section, the results of the previously mentioned methods are described. First, the results of the experiments are presented, followed by the results of the simulation.

5.1 Experiments

Two experiments were conducted, the first focusing on a kinetics study and the second an analysis of the kinematics of the walking gait.

5.1.1 Experiment 1: Kinetics study

Four participants were asked to participate in this experiment. The measured results are analyzed below.

The data of one of the participants can be seen in figure 18. The first graph shows the vertical capacitive relative signal (blue) as well as a boolean value which shows if the foot is in stance (1) or swing (0) motion (red). If the blue line is negative, it means that the center of pressure is on the back of the foot, while if the blue line is positive, the center of pressure is on the front side of the foot. If this value is roughly zero, it means the pressure applied is either centralized or the foot is not touching the ground. The relative center of pressure in the y-axis is calculated by subtracting the pressure value of sensor 2 from sensor 1 (figure 14b). The relative center of pressure in the x-axis (sensors 3 and 4) is not taken into account in this experiment.

The second graph in the figure shows the time of each step (blue). The red section of the bar shows the time of which the foot was on the ground, with a relative value given. As can be seen for this participant, the average time the foot is on the ground is 59.9% with a standard deviation of 3.9% of the step.

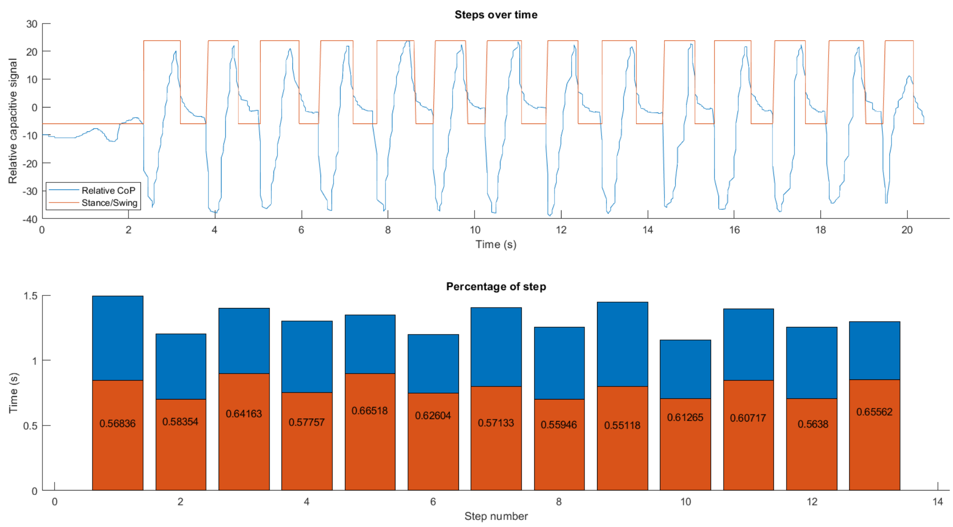

Figure 18: Kinetics results of one participant's steps

The average and standard deviations of all four participants are shown in figure 19. It can be concluded that the average stance time over step time is 61.2 % with a standard deviation of 5.9 %, which can be considered consistent.

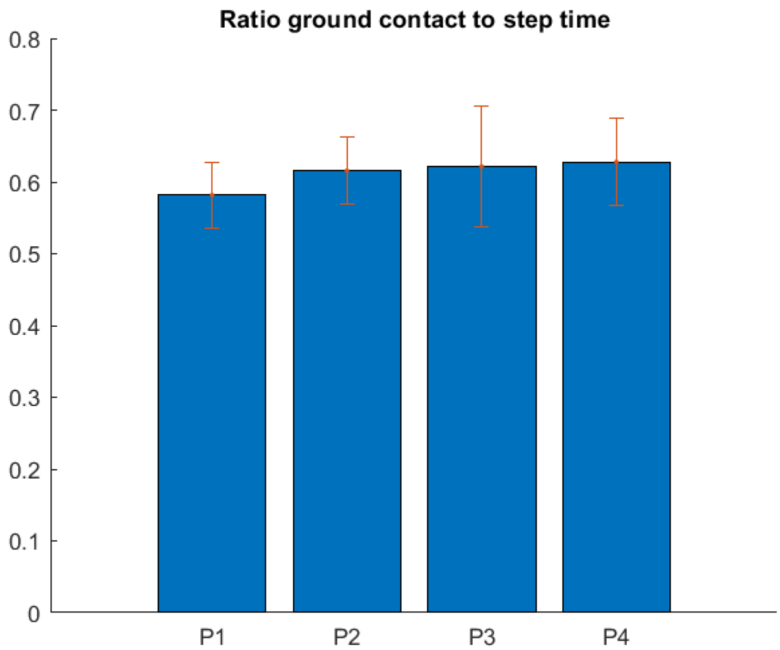

Figure 19: Ratio ground contact to step time for four participants

The other hypothesis is that the center of pressure during walking moves from the back of the foot to the front. This is indeed also the case, as can be seen for every participant.

5.1.2 Experiment 2: Kinematics study

During this experiment, eight participants were asked to walk on a treadmill at five different speeds varying from 3.5 km/h with steps of 0.5 till 5.5 km/h. Seven data points were recorded as shown in figure 15. However, during data analysis, the ASIS and hip points were not measured clearly for every participant. This is mainly due to the swinging of arms during the gait blocking the view for the cameras. Since these were not the most important measurement points and it was more important to get a most natural gait as possible, no changes were made during conducting the experiment.

From the data points, the knee angle with respect to the ground as a reference and the ankle angle with respect to the knee angle were calculated. This is plotted for different walking speeds per participant. It can be seen that the knee angle does not vary greatly with different walking speeds. However, the ankle angle varies slightly with different walking speeds for the majority of participants, with the absolute value of the ankle angle being bigger in both the dorsiflexion as well as planar flexion direction for faster walking speeds.

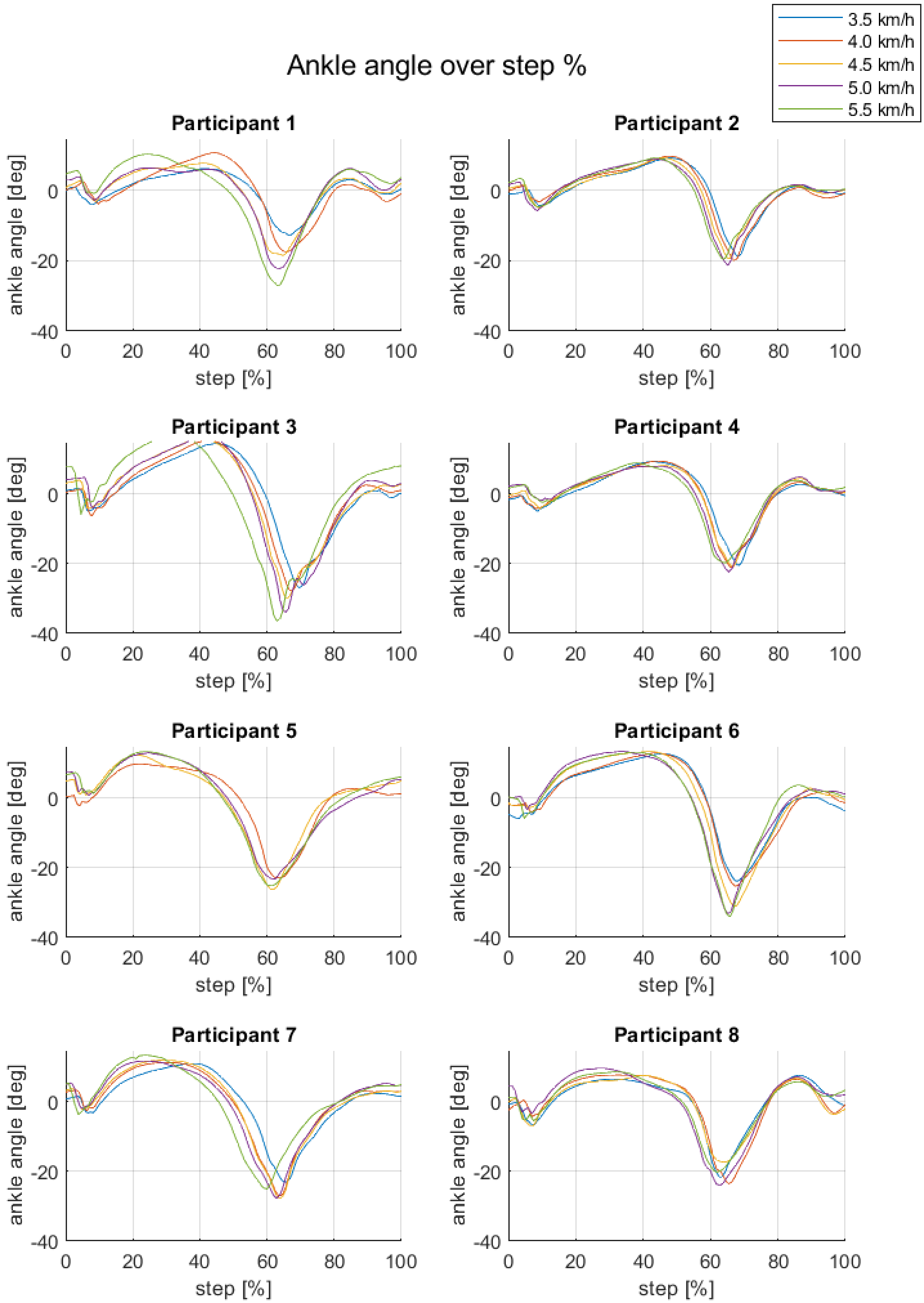

Figure 20: Ankle angles for the most average step of all participants at all five speeds.

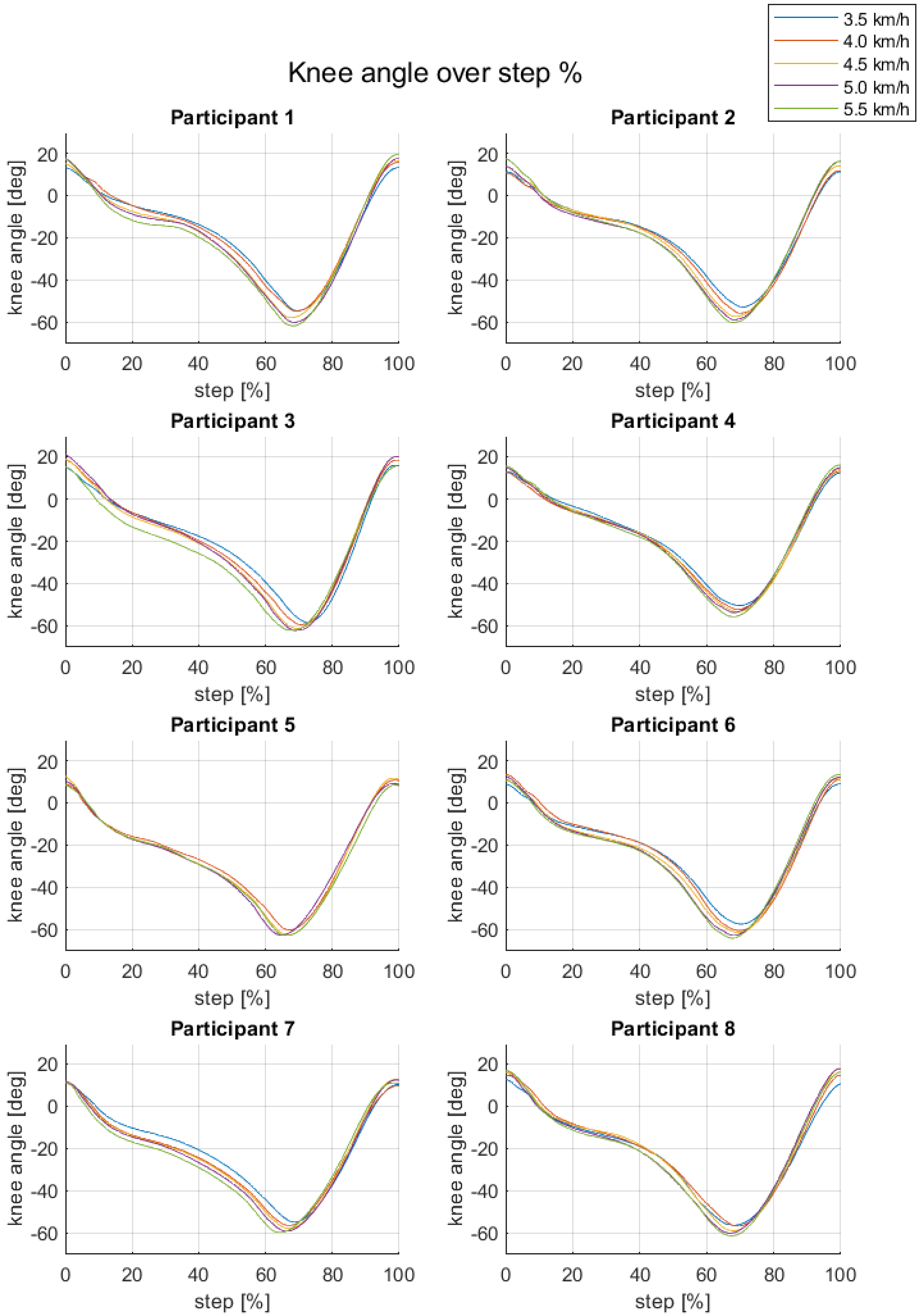

Figure 21: Knee angles for the most average step of all participants at all five speeds.

The most average step for every participant in every walking speed is determined, resulting in a total of 40 steps (eight participants multiplied by five walking speeds). The walking analysis of one participant at the slowest walking speed was found unusable, resulting in 39 walking gaits which were analysed. Comparing these to literature, the shapes and values look similar (Palmer 2002).

For all 39 gaits the knee motion in the x-direction, y-direction and angle are imported in MSC ADAMS. These are fitted to the simulation, ready for analysis.

5.2 Simulation

The simulation of the ankle prosthesis consists of two rigid links representing the foot and the lower leg. The links are connected by a torsion spring consisting of a variable damping and stiffness, which can both be tuned by the Tacit Learning System.

The foot consists of two links with a width and depth of 5 x 5 cm and a total length of 25 cm, and a density of 985 kg/m^3. It is initially modeled as two links with a fixed connection to better understand the difference in ground contact forces with the front and back of the foot. The lower leg has the same density but a variable height, dependent on the length of the lower limb of the participant, with a width and depth of 5 x 5 cm.

The ground reaction forces are modelled by an solid to solid impact function, a standard function implemented from MSC ADAMS. Mathematically, the function can be described as:

$$F = \begin{cases} 0 & \text{if } x > x_1 \\ k(x_1 - x)^e - c\dot{x} * STEP(x, x_1 - d, x_1, 0) & \text{if } x \leq x_1 \end{cases} \tag{10}$$

All variables are experimentally set. The values for x and x_1 depend on the foot and ground, and thus the distance in between these two solids. The stiffness k is set to $1.5E8$ N/m. The damping c is set to 10 Nm/s. The force exponent e is equal to 2.2 and the penetration depth d is equal to $1.0E4$ m. These values were chosen by trial and error, comparing the ground reaction force as a result of this MSC ADAMS simulation to the ground reaction forces of the OpenSim software.

The friction force is based on Coloumb friction, with several coefficients experimentally defined in MSC ADAMS. The static coefficient is set to 0.3, the dynamic coefficient is set to 0.1, the stiction transition velocity 0.1 and the friction transition velocity 1.0.

5.2.1 Concept

The idea of the Tacit Learning System is to create a better feeling during walking. The tacit learning parameters are the stiffness and damping of the ankle joint. A schematic overview of the control algorithm is shown in figure 22, where F_W represents the force induced by body weight.

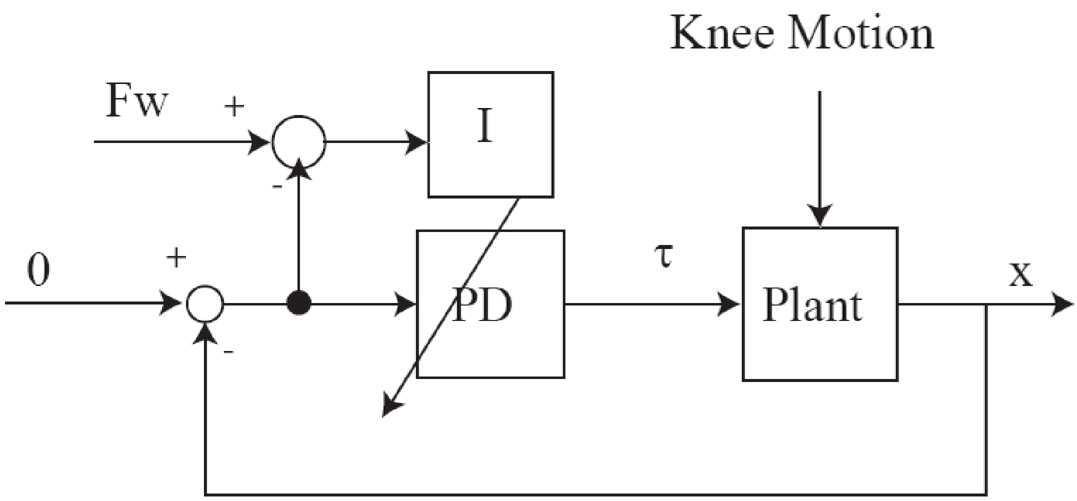

Figure 22: Schematic overview of the TLS control algorithm

The state variables used are the ankle angle, ankle velocity and force in the Y-direction working in the knee, which is in this case the same as the fixation point of the prosthesis.

$$x = \begin{bmatrix} \theta \\ \dot{\theta} \\ F_y \end{bmatrix} \tag{11}$$

The gains for the stiffness (K_P) and damping (K_D) can be combined as such:

$$\tau = \begin{bmatrix} K_P & 0 & 0 \\ 0 & K_D & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \theta \\ \dot{\theta} \\ F_y \end{bmatrix} \tag{12}$$

The gains for the stiffness and damping are variable, where the tacit learning coefficients are introduced: T_S and T_D are the tacit learning coefficients for the gain of the stiffness and the gain of the damping respectively. In equation, this can be written as:

$$\begin{bmatrix} \dot{K_P} \\ \dot{K_D} \\ 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 & T_S \\ 0 & 0 & T_D \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \theta \\ \dot{\theta} \\ F_y - F_w \end{bmatrix} \tag{13}$$

Completing the schematic control algorithm for the virtual ankle prosthesis.

The target area of the tacit learning system is during the stance phase, from the heel strike up until the maximum dorsiflexion of the ankle (see figure 23). This target area is chosen since the tacit learning system is to create the best feeling during walking, and during this phase, the stiffness and damping should have an accurate representation of the original ankle such that walking with the prosthesis feels natural. No additional torque has been added, therefore the phase from maximum dorsiflexion of the ankle until the toe-off will be left for future research. The swing phase is used to 'reset' the ankle to its original angle, to prepare for the next step.

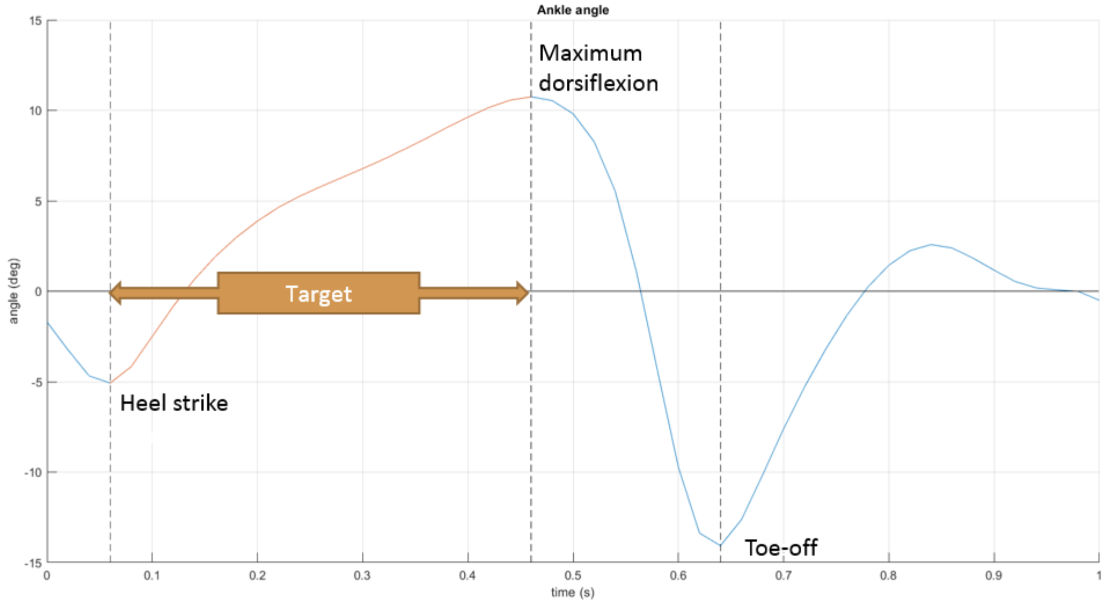

Figure 23: The target phase of the TLS

5.2.2 Limitations

Several simplifications have been made in the model which can be justified for the proof of concept. The first simplification is in the dimensions, only two dimensions are considered. The z-axis is left out since these movements are minimal during walking and do not have a significant effect on the outcome of the results.

Furthermore, the prosthesis is modelled as a rigid body with the same density properties as the human equivalent lower leg. The density properties of the current prostheses on the market have a similar weight (Jimenez-Fabian et al. 2012).

5.2.3 Initial results

Before implementing an algorithm that can adjust the damping and stiffness value, one needs to know how the damping and stiffness values are related to the force in acting in the knee, the force around which the algorithm is designed. Therefore, several damping and stiffness combination values are tested to see the result upon the force. The relation is shown in figure 24.

The y-axis represents the stiffness and the x-axis represents the damping, both in the ankle joint of the prosthetic leg. The color coding represents the third value, the force in Y-direction acting upon the knee. A low value, represented with the yellow color, can be seen on the top right, while a high force, the dark blue colored values, can be seen in the bottom left. This means that a low force correlates with both a low stiffness and damping, and a high force is necessary with a higher stiffness and damping. The relationship looks relatively linear with the stiffness effect having a factor five times more impact compared to the damping effect.

The black line in the graph represents the optimal value for an average human with a body weight at roughly 800 Newtons. This means that a combination of the stiffness and damping on the black line yields in an optimal walking gait.

With this graph, it becomes more clear what the effect of the stiffness and damping actually result into. If the stiffness and/or damping is too high, the knee has to act out a higher force on the prosthesis to still be able to have a normal walking motion. Imagine walking in a ski boot, the ankle is in a fixed position and in order to have a normal walking gait, one needs to act out a lot more force in order to be able to walk properly, therefore the gait is adjusted and walking in a ski boot is deemed uncomfortable. This effect also happens when the stiffness and/or damping of the prosthesis is too high.

On the other end of the spectrum, if the damping and/or stiffness is too low, one needs to act less force to create the same motion. This is also not desired, since one cannot control its own body weight. Imagine if your ankle is a loose hinge, with no counter force to counter-balance your weight, you would tip over, which is also not desired while walking.

These main principles are used to further construct the basis of the Tacit Learning System. Initially, the normal force on the knee in the Y-direction is set equal to the body weight of the person, minus the roughly two kilogram of lower limb, which is below the knee and thus does not have an effect.

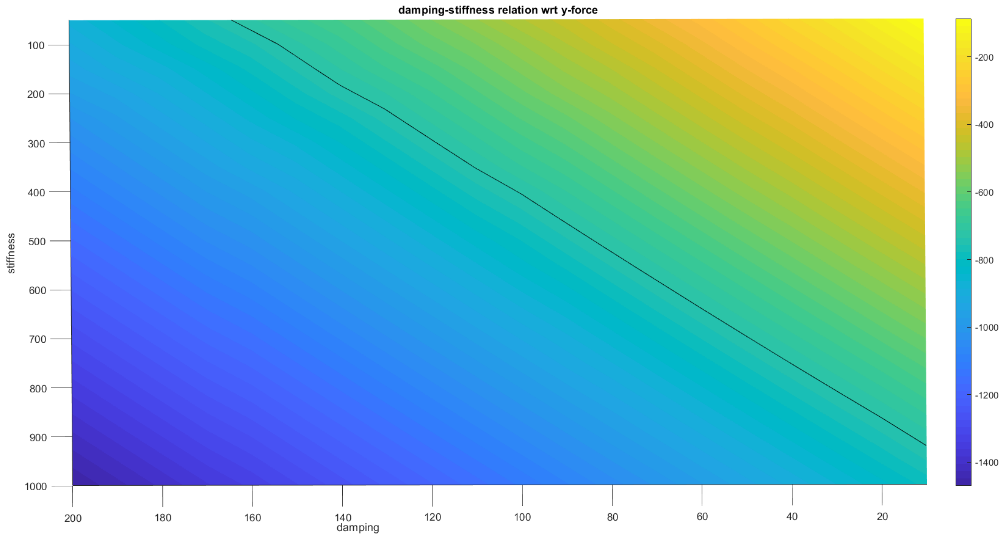

Figure 24: The dependence of the force based on the stiffness and damping.

Stanford's OpenSim software is used to generate walking gait data, out of which the knee motion is used for the guidance of the MSC ADAMS model. A simple Tacit Learning System algorithm is used for damping optimization within the prosthesis. A tacit learning coefficient of 0.2 normalized to the average walking speed is used to create a single damping value updated after every step walked by the prosthesis.

The results of this algorithm is shown in figure 25. The walking speed is changed after every ten steps instantaneously to see the effect of the TLS algorithm. The first graph represents the damping value over every step walked, while the second graph shows the error of that same walked step. It can be seen that it takes the prosthesis about four steps of walking to set the error to zero, thus finding an ideal damping value for the speed.

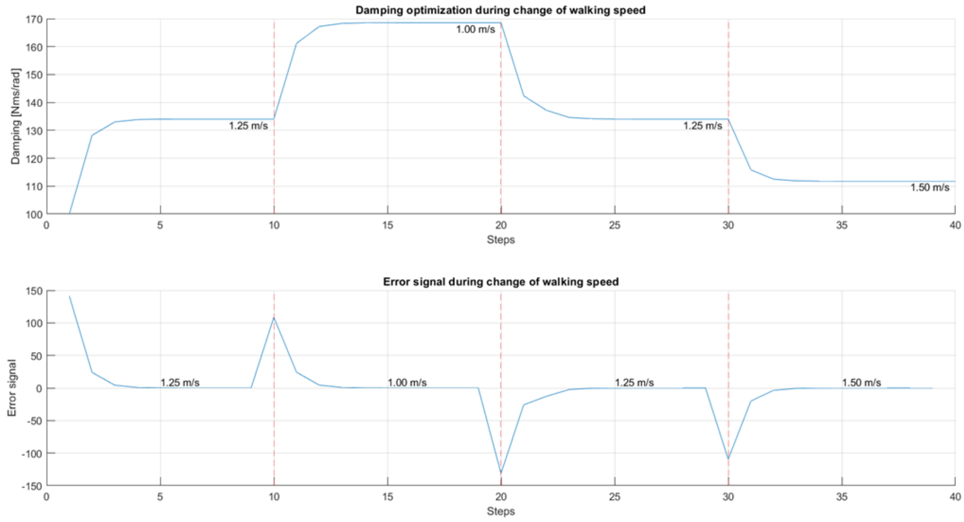

Figure 25: Initial results of damping optimization with OpenSim data.

5.2.4 Results control scheme 1: Damping optimization

After initial testing with OpenSim results, the algorithm has been updated significantly. Firstly, the algorithm is adapted to change during the walking step, rather than after every step walked. This means that instead of creating one damping value per walked step, the damping is changing constantly to adjust for changes and converges to a pattern rather than a single value. Next to this, three control schemes have been developed: one to only adjust for damping keeping the stiffness constant, the second to adjust the stiffness while keeping the damping constant and a third control scheme updating both damping and stiffness at the same time.

The results for the first control scheme, damping optimization, are shown in the following graphs. The stiffness tacit learning coefficient is set equal to zero while the damping coefficient is set to 0.5. Figure 26 shows the damping value in Nms/rad for five steps. It is chosen to only show one participant's results in figures, while the results for the other participants show a similar pattern.

Each graph shows the development of the damping value over time for a different walking speed, starting with the top graph at 3.5 km/h, while the bottom graph shows the results of walking at 5.5 km/h. For this participant, it can be seen that the shape per step finds an equilibrium.

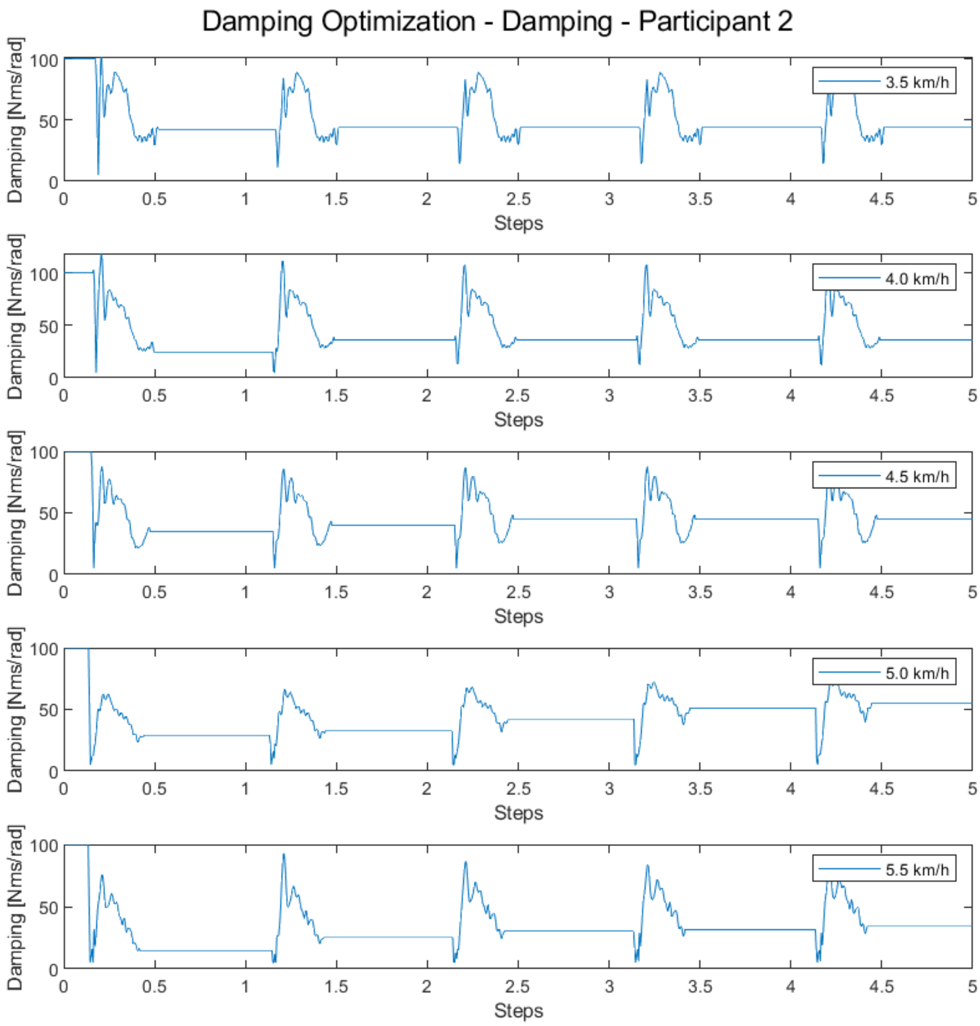

Figure 26: Results of damping factor from TLS control scheme 1.

For 5.0 km/h and 5.5 km/h, it can be seen that a slight offset occurs with every step. Especially with 5.0 km/h this offset seems to be relatively large compared to the other values. This is also visible in the error calculations.

More importantly to see if the TLS works, the error graph should be analyzed. These values are given in Newton, since it is the force difference between the body weight and the actual force acting on the knee. As can be seen in figure 27, for every speed at the first step, a big spike is shown. This is the result of an inaccurate starting value of the TLS. Over the steps, the error signal fluctuates around zero in the target area, meaning the TLS has a positive effect on the system.

For this participant, the sum of the error in the first step walking at 3.5 km/h is 1663 N with the largest absolute error in one time step being 169 N. The sum of the error after 5 steps is 1181 N, with a largest absolute error of 72 N. Table 1 shows these values for all five walking speeds for this participant. Except for 5.0 km/h, all sum of errors have decreased in value. As seen in the damping value, this is due to an offset with every step.

Walking speed	First step sum of error	First step peak error	Fifth step sum of error	Fifth step peak error
3.5 km/h	1663 N	169 N	1181 N	72 N
4.0 km/h	1864 N	236 N	1345 N	85 N
4.5 km/h	1708 N	303 N	1383 N	121 N
5.0 km/h	1612 N	589 N	1680 N	406 N
5.5 km/h	2321 N	541 N	2033 N	274 N

Table 1: Error results of participant 2.

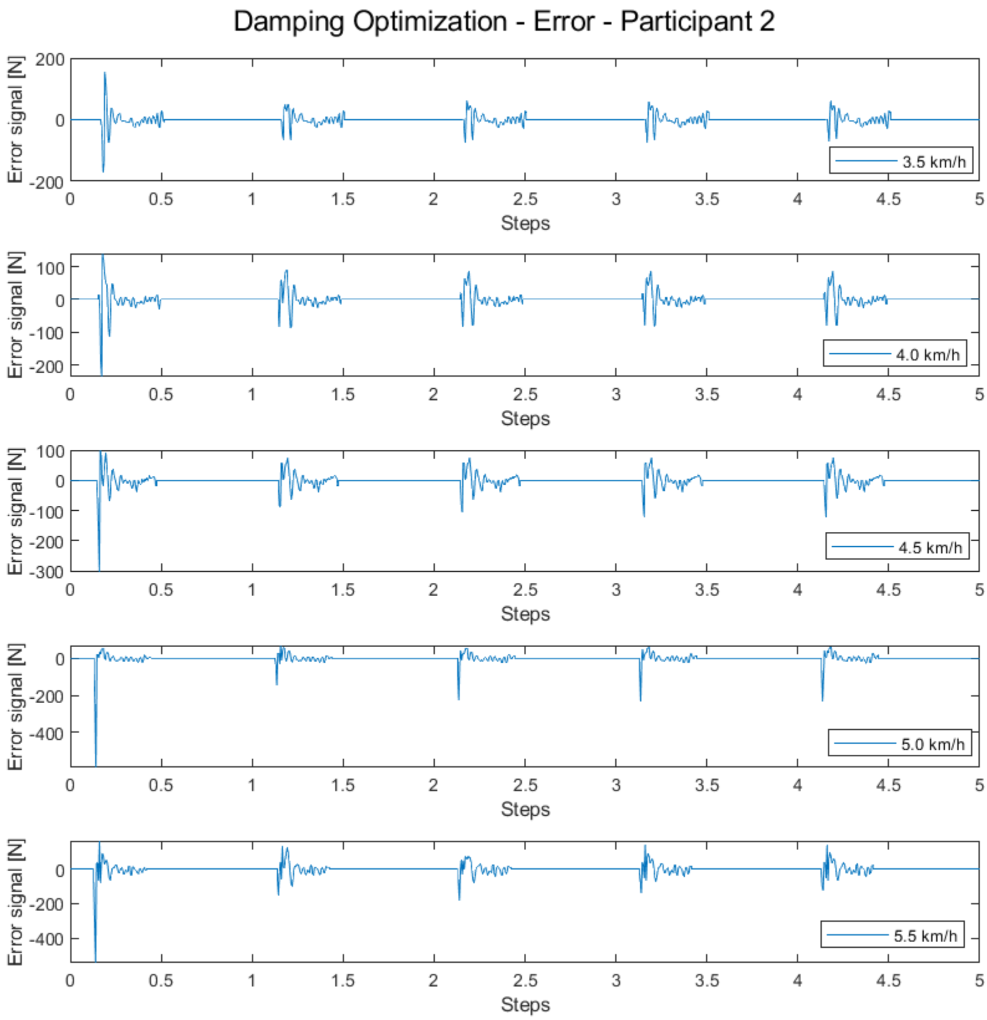

Figure 27: Results of error from TLS control scheme 1.

The next figure that is analyzed is the y-force in the knee during these steps. The results are shown in figure 28. An inverse peak is shown equal to the force induced by body weight of the participant, just as expected from the literature studies (Winter 1987).

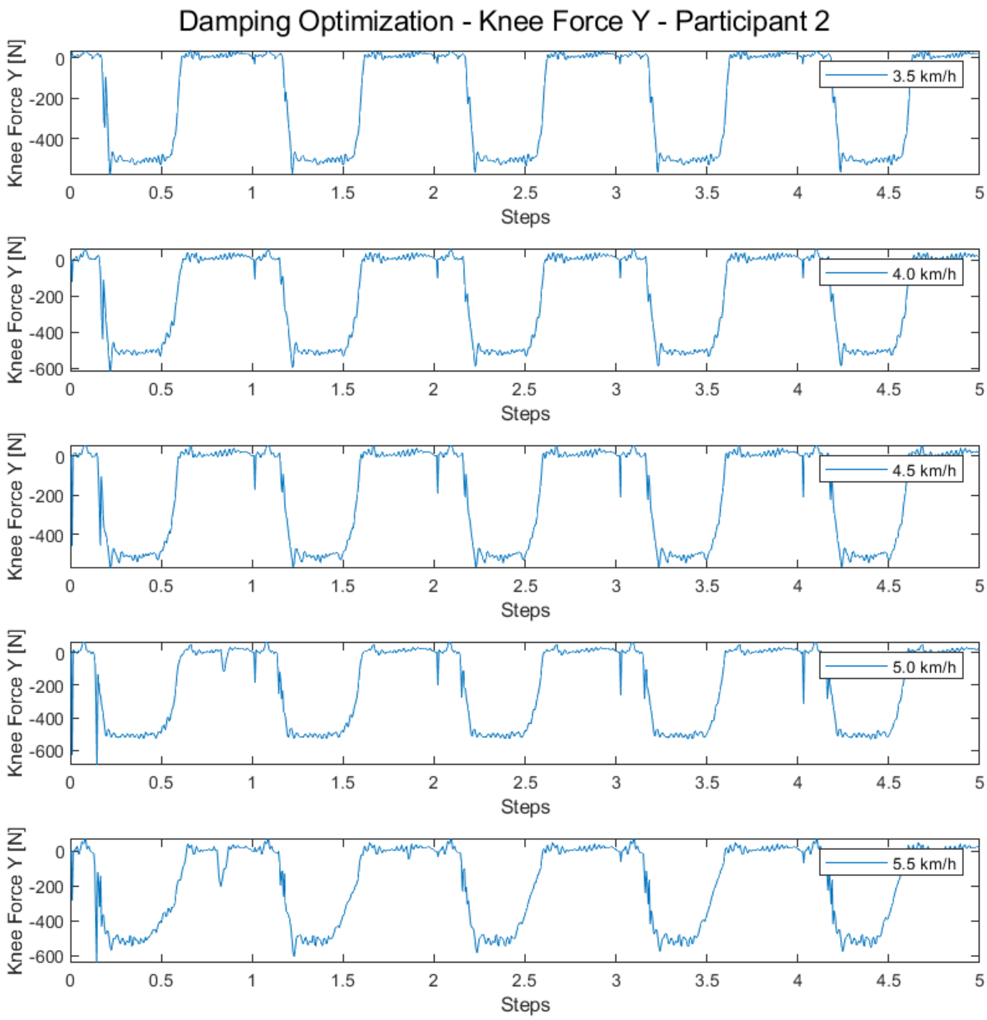

Figure 28: Results of knee force in y-direction from TLS control scheme 1.

To compare with other participants, the averages are shown in table 2 for each walking speed. The first line shows the walking speed, the second the mean of the error in the fifth step divided by the error in the first, as a sum of the errors for all individual participants. This shows a value below 1 if the error in the fifth step is lower than the error in the first step, like desired, and a value above 1 in the opposite case. The third and last line of the table shows the standard deviation.

Only for the normal walking speed, at 4.5 km/h, the algorithm seems to have the desired output, however the standard deviation seems relatively high. This is due to the fact that with half of the participants, the algorithm works pretty well and with the other half it does not. Looking at the individual participant's results, the algorithm works better with a slower walking speed compared to a faster walking speed.

Walking speed	3.5 km/h	4.0 km/h	4.5 km/h	5.0 km/h	5.5 km/h
mean of fifth error / first error	1.02	1.07	0.89	1.14	1.27
Standard deviation	0.35	0.42	0.39	0.47	0.31

Table 2: Mean error results of all participants for damping optimization.

5.2.5 Results control scheme 2: Stiffness optimization

The second algorithm that is tested has the damping tacit learning coefficient set to zero while the stiffness tacit learning coefficient is set to 0.2. The results are shown in the same way as the first TLS algorithm. Figure 29 shows the change in stiffness over time. The stiffness graph for each of the different walking speeds converges to a single peak per step. There is a clear difference to be seen comparing the first, unoptimized step and the fifth step.

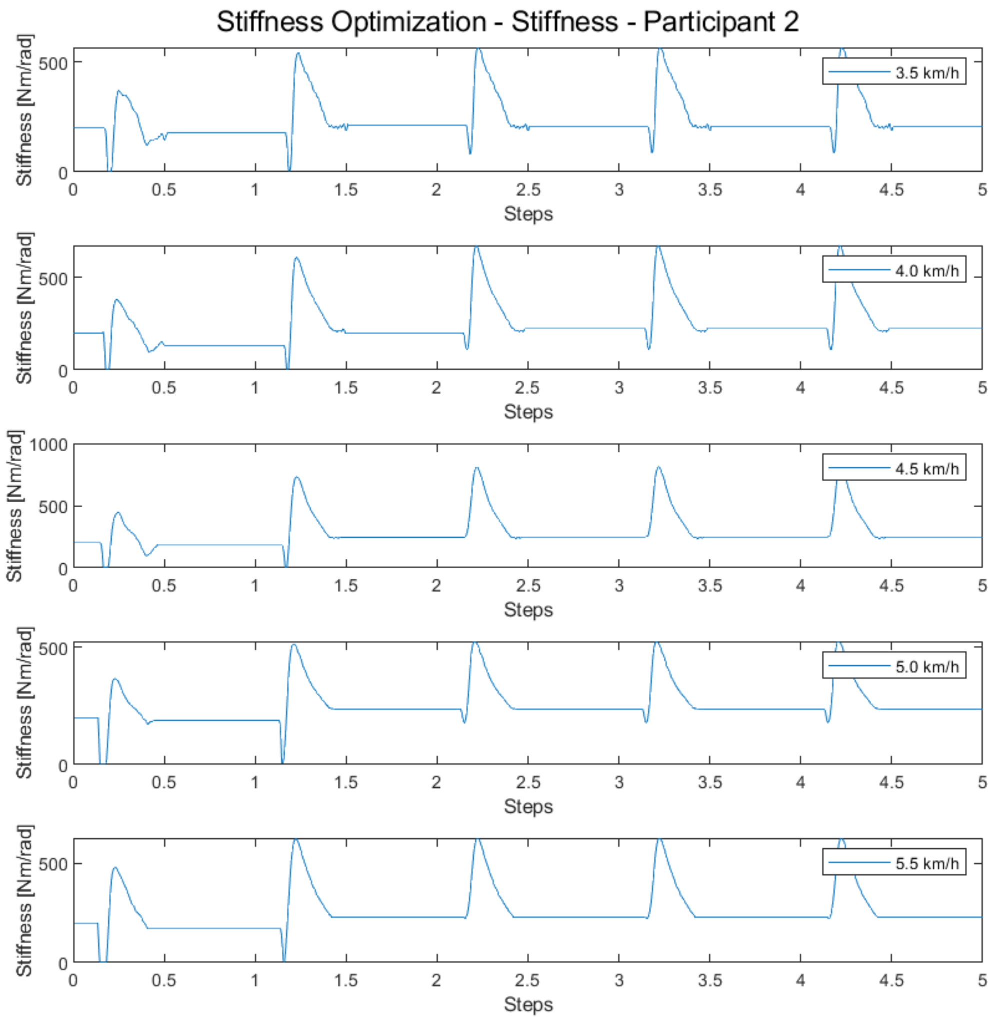

Figure 29: Results of stiffness factor from TLS control scheme 2.

Figure 30 shows the error changing over time. Just like the first algorithm, the error is based on the force difference of the force working in the Y-direction of the knee force and the expected force based on the body weight. The error only appears when the TLS algorithm is in the active phase. The error of the stiffness optimization algorithm shows a clear difference with the first step and the following steps, decreasing the error over time. This shows the positive effect of the tacit learning algorithm.

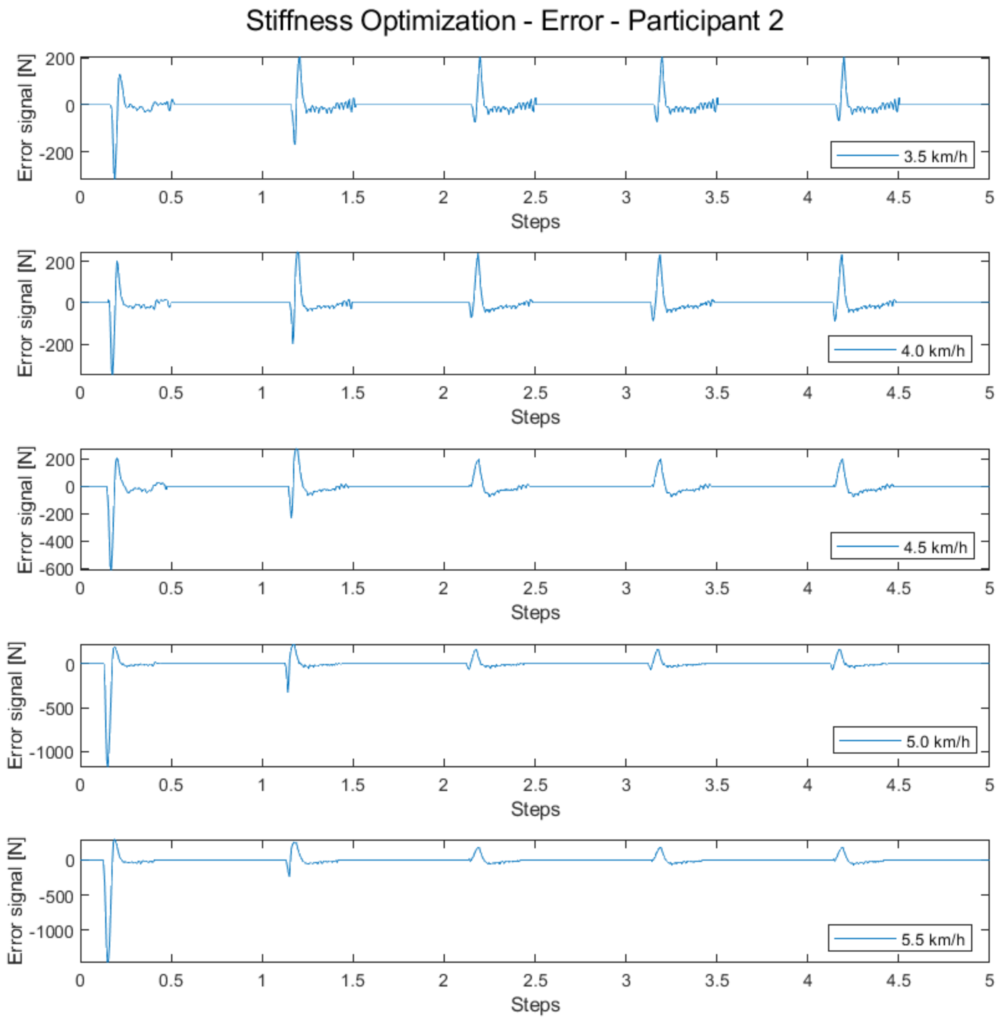

Figure 30: Results of error from TLS control scheme 2.

Figure 31 shows the force working in the Y-direction on the knee over time. This, much like the first TLS algorithm, looks much like the expected results from literature (Winter 1987). A relatively large peak is shown during the first step, especially at high walking speeds. This is an indication of a too high stiffness in the prosthetic ankle.

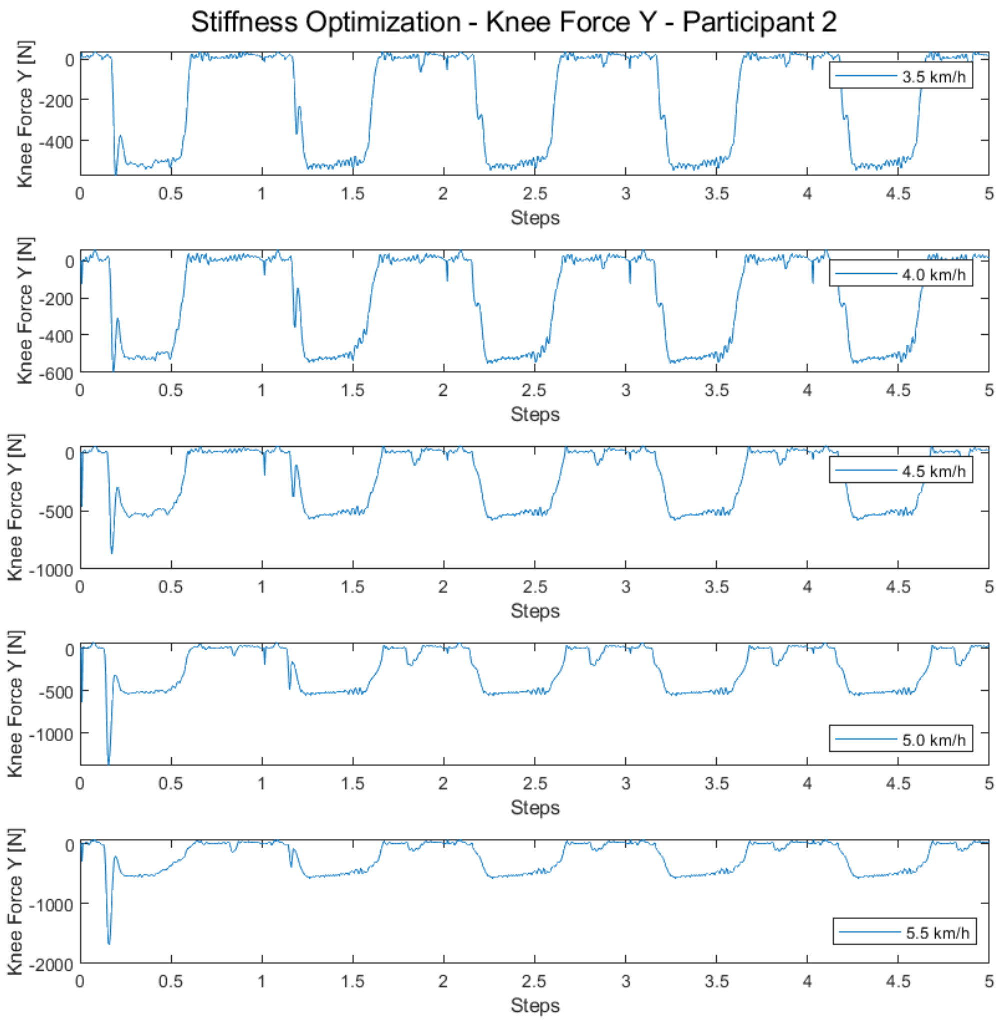

Figure 31: Results of knee force in y-direction from TLS control scheme 2.

Combining the results of all participants, this TLS control scheme shows a positive effect in all cases as can be seen in table 3. The standard deviation is in most cases also lower than the first TLS control scheme, meaning a more stable result. Furthermore, looking at all individual results, the algorithm is only worse in two cases (participant 4 at 3.5 km/h and participant 6 at 5.5 km/h). Therefore, this control scheme seems to be working a lot better than the first control scheme.

Walking speed	3.5 km/h	4.0 km/h	4.5 km/h	5.0 km/h	5.5 km/h
mean of fifth error / first error	0.73	0.59	0.47	0.50	0.35
Standard deviation	0.28	0.21	0.27	0.46	0.29

Table 3: Mean error results of all participants for stiffness optimization.

5.2.6 Results control scheme 3: Damping and stiffness optimization

The third control scheme tested is with both damping and stiffness tuned at the same time. The stiffness tacit learning coefficient is set to 0.1, while the damping tacit learning coefficient is set to 0.3.

The damping results are shown in figure 32 and the stiffness change over time in figure 33. For both damping and stiffness, it converges to a shape per step. However, not only do the shapes look different compared to the previous control schemes, the shape changes more significantly with the walking speed. This can mainly be explained by the two variables used and thus resulting in several different optimal shapes.

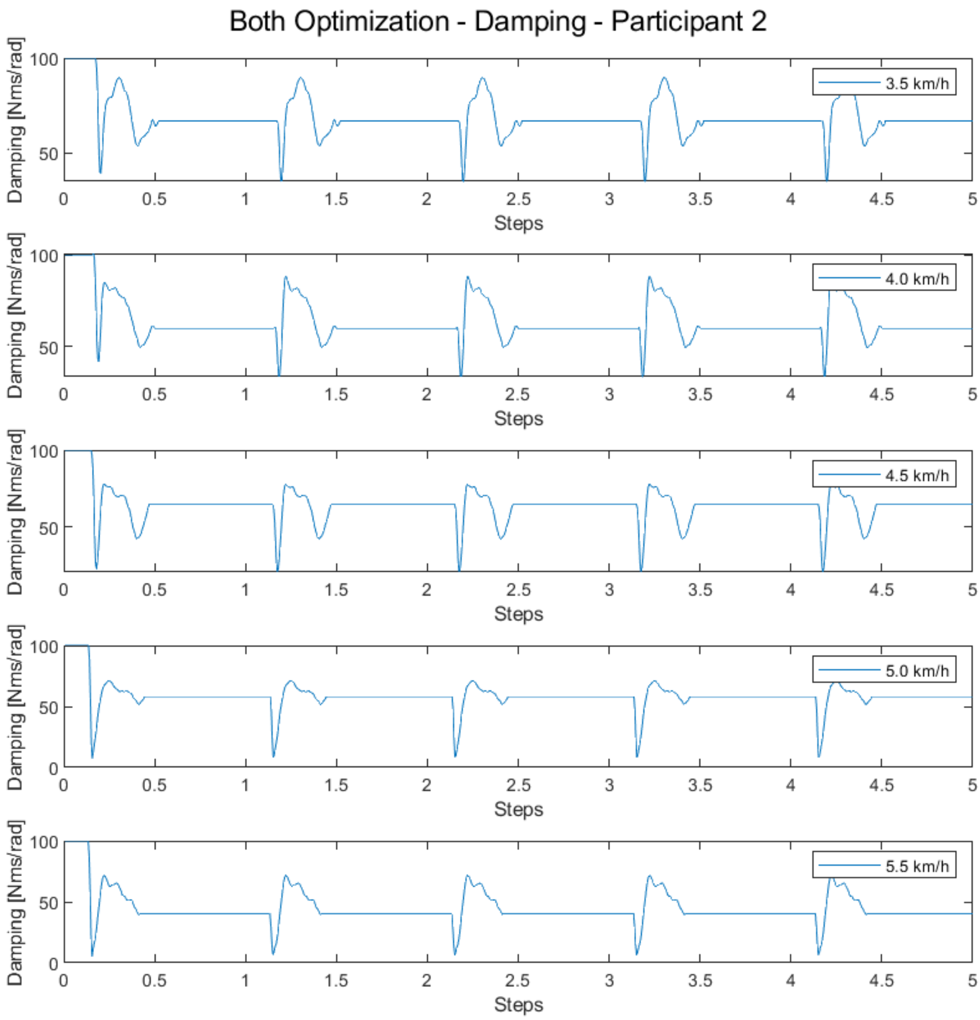

Figure 32: Results of damping factor from TLS control scheme 3.

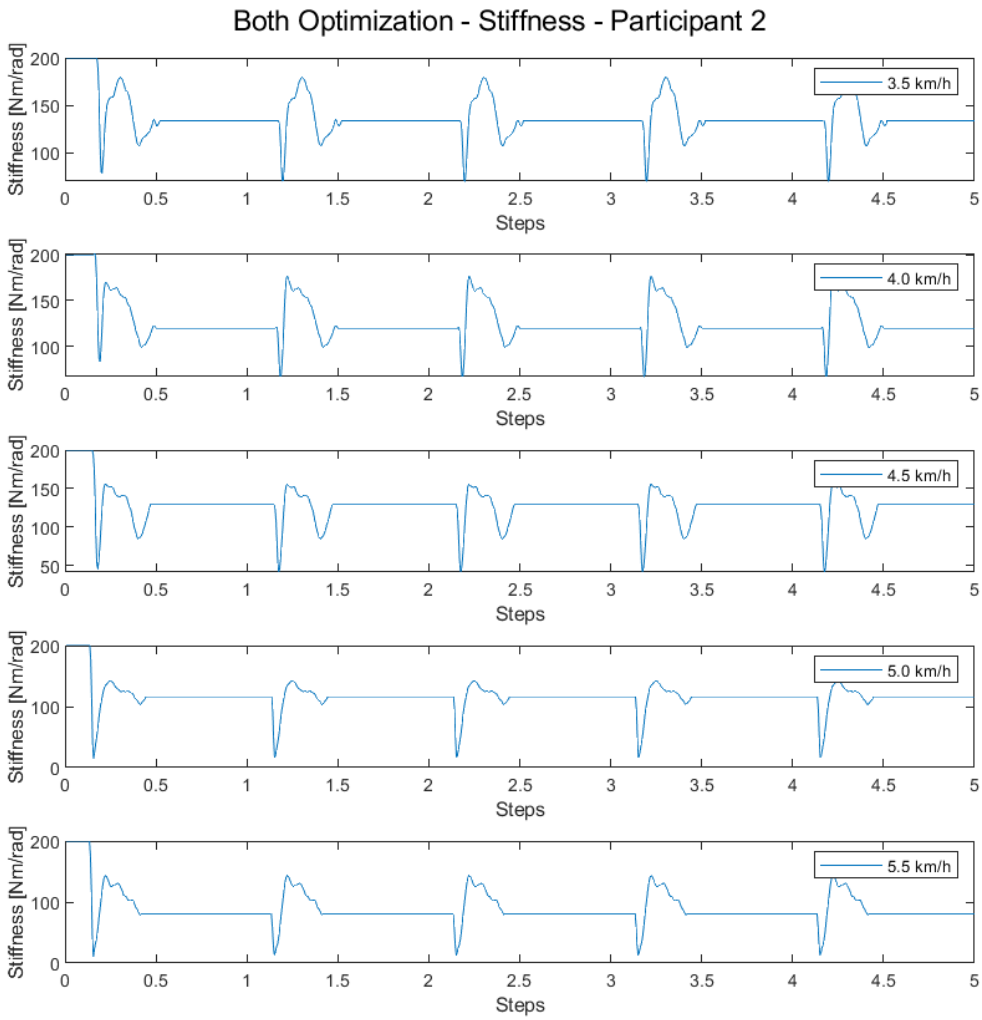

Figure 33: Results of stiffness factor from TLS control scheme 3.

In figure 34, the error over time is shown for the third control scheme. Similar to the previous two control schemes, the error seems biggest during the first step and improves with every step taken.

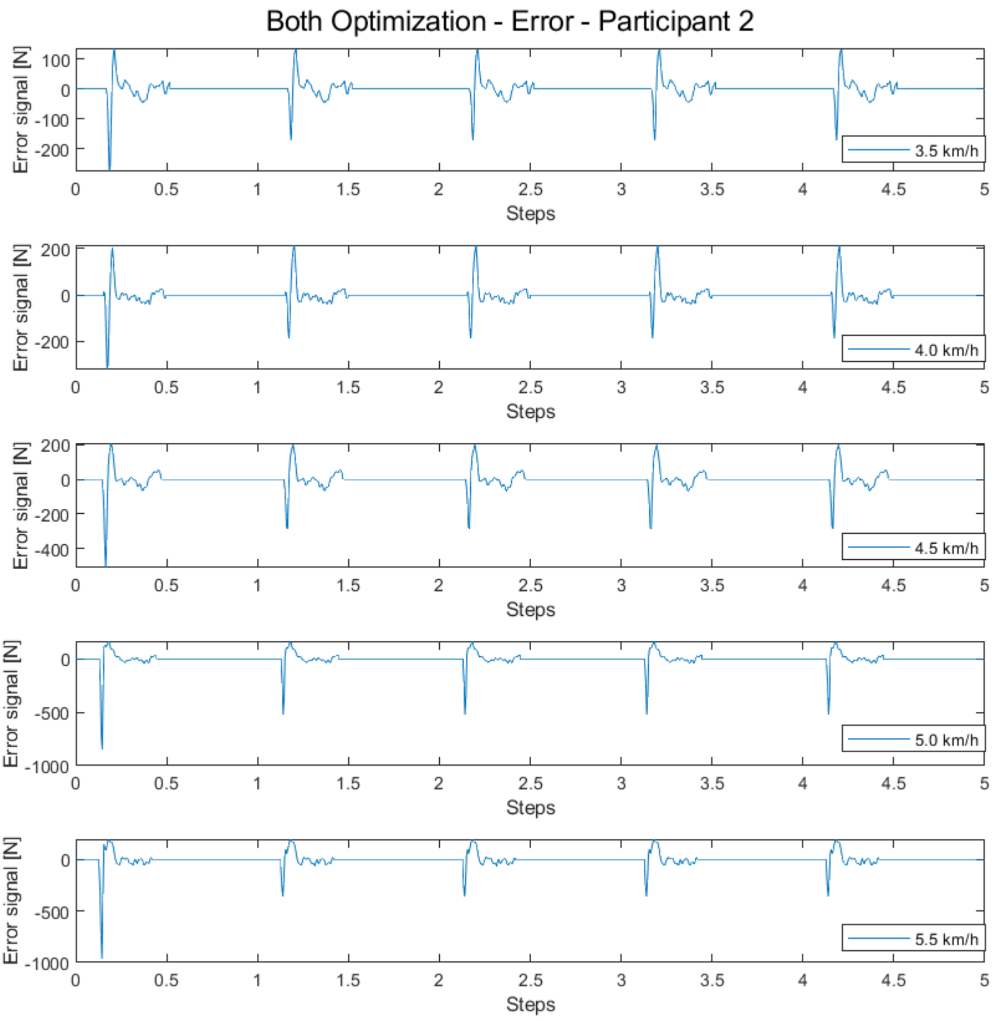

Figure 34: Results of error from TLS control scheme 3.

The force in the knee in the y-direction is shown in figure 35. Similar to the second control scheme, with a higher speed, a spike appears at faster walking speeds. Again, this is most likely the result of a too high stiffness in the initial step.

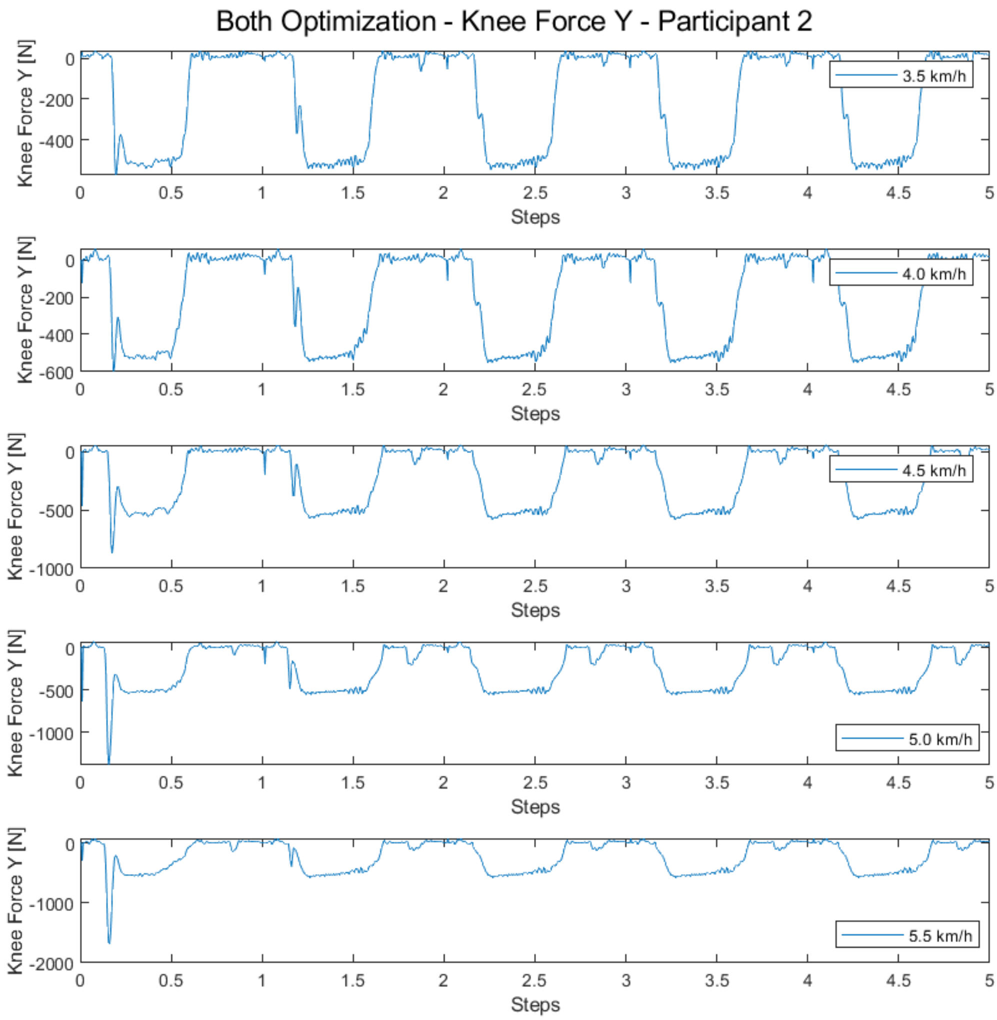

Figure 35: Results of knee force in y-direction from TLS control scheme 3.

The results of this TLS control algorithm are summarized in table 4. In every case, the control scheme had a positive effect on the system with a relatively low standard deviation.

Walking speed	3.5 km/h	4.0 km/h	4.5 km/h	5.0 km/h	5.5 km/h
mean of fifth error / first error	0.86	0.85	0.85	0.90	0.84
Standard deviation	0.17	0.13	0.11	0.27	0.25

Table 4: Mean error results of all participants for both optimization.

6 CONCLUSION

To conclude if the Tacit Learning System is a valid control algorithm for the ankle prosthesis, first the research questions as stated in the introduction must be answered.

The first research question relates to the complexity of the model. As explained in section 4.2, MSC ADAMS is used to model the prosthesis. The lower leg and the foot are represented by two rigid links, linked together with a torsion spring, resembling the ankle. The torsion spring has a variable stiffness and damping.

Several simplifications had to be made, as will be discussed more elaborately in the discussion section, but overall a reasonable simulation has been used during this thesis. This simulation is mainly tested with data gathered through OpenSim, which provided accurate data for the walking motion.

Since it is found in literature that the main problem relates to the feeling during walking, the main focus is put on the stance phase, more specific from the initial ground contact up until the maximum dorsiflexion of the ankle. Therefore, the control algorithm is neglecting a significant part of the walking motion, the push-off created by the toes. No active torque is used to help during the walking motion, which means that an ideal prosthesis cannot be developed. However, due to time and complexity constrains, this is something that can be further developed in follow-up research.

For the scope of this thesis, it can be concluded that an ankle prosthesis can simply be modeled using MSC ADAMS, creating two links with similar properties to a human lower leg and foot, and connect those by a torsion spring with variable stiffness and damping.

The second research question relates to the optimization parameters. Since the simulation is modeled based on kinematics rather than kinetics, the kinetics therefore can be used as optimization parameters. Since the kinematics guide the motion initially, these cannot be considered for choosing the optimization parameters.

Therefore, the different forces which are applied onto the prosthetic simulated lower limb are analyzed. During this thesis, it was found hard to estimate internal forces within the leg, making it hard to estimate the stiffness and damping parameters since the internal ankle torque is unknown.

One of the forces that can more easily be analyzed was the force acting upon the knee, or the upper part of the prosthesis. Knowing that during the stance phase, a normal force equal to the force induced by body weight is necessary for a realistic walking motion, this factor is used to base the optimization parameters on.

The third and last research question focuses on the correct criteria to define of the Tacit Learning System works accurately for an ankle prosthesis. These have been described in section 4.2: the main criterion relates to the force acting in the knee as well as the ground contact forces.

During the analysis of the results, the error, mainly related to the force acting in the Y-direction in the knee, is used to see if the Tacit Learning System is improving the walking gait significantly.

It was found that, during the first control scheme with just damping optimization, the TLS is only improving the walking gait with half of the participants. From this, it has to be concluded that this control scheme is not deemed successful in the way it is used now. Several improvements can be made, which will be elaborated upon in the discussion section.

The second control scheme, optimizing the stiffness parameter, deemed the most successful. In 37 out of the 39 (95%) cases tested, the TLS was able to improve the walking gait significantly. The results with this control scheme also were more reliable, as can be deducted from the lower standard deviations.

The third and last TLS-based control scheme tested is optimizing both the damping and stiffness at the same time. In most cases, especially at lower walking speeds, this control scheme is deemed significantly improving the walking gait. However, at higher walking speeds, in more cases the control system was not able to optimize the walking gait properly, while still on average being able to improve. This control scheme therefore in its current form seems somewhat successful, however, several improvements need to be made before continuing.

To give an overall conclusion of this thesis, a successful model of the ankle prosthesis has been built that works with the Tacit Learning System. The Tacit Learning System can significantly improve the walking gait, and thus reduce the energy used by human metabolism, by optimizing the stiffness in the prosthetic ankle. Further research has to be conducted to conclude if including damping within this algorithm has a positive effect.

7 DISCUSSION

In this section, several aspects of this thesis will be discussed. First, the effects of creating a model instead of using an actual prosthesis are discussed. Second, the simplifications of the model will be elaborated upon and their effect on the end results will be explained. Next, the TLS algorithm and its limitations are discussed. Last, ideas for further research studies are given and how one would continue this project.

Initially, it was chosen to do a simulation study rather than working with an actual prosthesis. The main reason for this decision is that there was no actual prosthesis available. Second, testing with amputees would take too long for the available time span due to regulations in Japan. Furthermore, by using a simulation, updates and revisions can be evaluated instantaneously giving more freedom of design.

To prove if a control algorithm is increasing the human metabolism in a simulation is challenging, since there is no way of testing the human metabolism during simulated experiments. Therefore, other ways of testing had to be thought of, which was quite time-consuming. Furthermore, it is therefore never for sure accurately to be said if the Tacit Learning System actually improves the human metabolism by only looking at a simulation, so further research needs to be conducted with an actual prosthesis. However, I do believe that this thesis gives a decent foundation of the capabilities of the TLS algorithm with an ankle prosthesis, and this initial study is valuable for further research in this area.

Creating a model of a human (prosthetic) ankle comes with certain simplifications. One of these simplifications is that the foot and lower limb are both modeled by single rigid body links with same density and material properties as the human variant. No heel indent is modeled and there is limited flexibility in the leg used. Furthermore, the ground reaction forces might not be completely optimal as used in the simulation, since this always has a deviation from reality.

Using the input parameters in the first case from OpenSim, the data has slightly been adjusted to fit the MSC ADAMS model better. Some roughness is removed from the data making the input and thus the output smoother. Furthermore, the data has been extrapolated for different walking speeds, and are thus less accurate again. However, this has only been done in the first analysis and the experimental data from the participants has not been tweaked.

Other simplifications made can be found in the control algorithm. For the optimization parameters it is mainly based on the force induced by body weight. It is known that in motion, the Y-acceleration of the center of mass also has an effect on this force. However, this is neglected since the effect is significantly small in comparison to the force induced by body weight. Therefore, it is believed that this effect does not vary the end-conclusion greatly. It might affect the values of the results slightly, but not significantly to draw a different conclusion. However, improving the optimization parameters in the control algorithm can definitively be studied in further research.

The algorithm used is based on Tacit Learning coefficients. These coefficients have to be tweaked as good as possible, just like any other control algorithm. A lot of time during this thesis is spent just tweaking these values and looking at the updated results. However, for all participants, the same algorithm and thus same coefficients are used. It might be worthwhile in further research to experiment with tweaking these values based on individual subjects and doing more research into the effect of these coefficients on the system as a whole.

As mentioned in the conclusion, the Tacit Learning System can significantly improve the walking gait, and thus reduce the energy used by human metabolism. The second control scheme, by optimizing the stiffness, seems the most fruitful out of the three analyzed in this thesis. The next step would be to analyze this control scheme with an actual prosthesis.

Furthermore, the other control schemes as described can be analyzed with an actual prosthesis as well. Even though these do not work with every case in simulation, during experiments a different conclusion can be drawn. Especially since the all control schemes work quite well in different situations, these should not be completely neglected in further research.

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