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**A multi-sensor, hybrid model- and signal-based
control system for powered lower limb
prostheses**

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Abstract

Humans have come a long way in the efforts for mobility restoration, but, as many primary solutions, these breakthroughs suffer from long-term secondary side effects. Today's prosthetic technology is much more advanced than the early days of wooden substitutes. And yet, when it comes to prosthetic legs, the basic principle still remains the same - attaching a fixed rigid body, albeit with some spring and damper properties, to the residual limb. Since the user has no intrinsic control over it, they adapt to these foreign bodies using compensatory movements. This in turn causes long-term complications due to increased loads and wear and tear of the parts used for adaptation. The aim of this dissertation is to address this need and develop a below-knee prosthesis controller, which includes the user in the prosthesis control as a way to bridge the performance gap between below-knee prostheses and their biological counterparts, thus reducing the long-term effects due to compensatory movements. I have first developed an algorithm that predicts desired ankle kinematics and stiffness based on high-density electromyography signals, which was intended to be used as the user's input to the prosthetic controller. This algorithm was successful in providing users with voluntary position and stiffness control, assessed with a virtual target matching task, as well as provide reasonable estimates for kinematics and ability to control stiffness during locomotion. Following this, a prosthetic control strategy, providing consistent cyclical gait oscillations, which are modulated by this user input, was devised. Further technological advancements were needed for the implementation of high-density sensor system with real-time prosthesis users. This led to the development of a wearable high-density electromyography and inertial measurement unit system, a real-time software solution, and a custom mobile application, along with other required data collection hardware. The solutions were further tested and validated, and a comprehensive locomotion dataset including all these signals along with motion capture and force plates data was collected using the setup. This dataset was used to train the final prosthetic controller and assess its performance. The end results demonstrate that the approach's accuracy is comparable to the most current prosthetic controllers. However, it additionally provides the ability to generalize between people, output torque and position for both sagittal and frontal planes, additional stiffness control, and provide a unique ability that grants users with volitional control during non-loading and standing conditions as well as stable gait control during locomotion. This presents an opportunity for the prosthesis to adapt and comply to its user's needs instead of the other way around.

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This PhD has been a great journey, which was definitely enriched by the people I have met along the way and the bonds that we've built. Reflecting upon it here, I would like to express my tremendous gratitude for all the support and happiness that these people have brought into my life for these past few years.

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Dedication

In memory of my mom, to whom I owe everything I have achieved. I only wish she was around to share these pivotal events with and try to repay her. Since this is not a possibility, I shall dedicate my efforts to honour all the selfless love and support she had given me throughout her life.

Glossary

5-HT 5-hydroxytryptamine

AMI Agonist-antagonist myoneural interface

ANOVA Analysis of variance

CPG Central pattern generator

DLR Diencephalon

DoF Degree-of-freedom (plural, DoFs, for degrees-of-freedom)

EDL Extensor digitorum longus

EHL extensor hallucis longus

EMG Surface electromyography

FDL Flexor digitorum longus

FHL Flexor hallucis longus

FSC Finite-state controller

GL Gastrocnemius lateralis

GM Gastrocnemius medialis

GRF Ground reaction force

HDEMG High-density surface electromyography

ID Inverse dynamics

iEMG Intramuscular electromyography

IK Inverse kinematics

IMU Inertial measurement unit

LED Light-emitting diode

MLR Mesencephalon

MRRN Middle rhombencephalic nuclei

NMF Non-negative matrix factorization

OA Osteoarthritis

PRRN Posterior rhombencephalic nuclei

PT Peroneus tertius

RMSE Root mean square error

RPNI Regenerative peripheral nerve interface

SNc Substantia nigra, pars compacta

SOL Soleus

SRS System requirements specification

TA Tibialis anterior

TMR Targeted muscle reinnervation

TP Tibialis posterior

URS User requirements specification

VTa Ventral tegmental area

XCOR Cross-correlation

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Chapter 1

Introduction

Limb amputation impacts millions of people around the world [1, 2, 3, 4] with the most prevalent level of amputation being below-knee (transtibial) [1, 2]. A large part of this epidemiology is due to the fact that most transtibial amputations are caused by devascularization [5], a main consequence of diabetes [6, 7]. As the rates of diabetes and the age of the population are predicted to increase [8, 9, 10] so is the rate of below-knee amputations [1, 2].

Following an amputation, a person undergoes rehabilitation, including a choice - and fitting - of a prosthesis [11]. However, shortcomings in capabilities of transtibial prostheses, compared to their biological counterparts, still cause medical complications and functional deficit years after the amputation. Such prolonged use of prostheses causes an abnormal gait [12], resulting in changes in joint and spinal loading. This leads to increased cartilage wearing and subchondral bone remodelling [13], resulting in increased rates of knee and hip osteoarthritis (OA) compared to non-amputees [12, 14, 15, 16], as well as long-term spinal problems [17]. A major reason for this is that neither passive nor semi-active prosthetic systems are able to meet the energy requirements during locomotion [18, 19]. The reason being that the musculoskeletal system comprises not only the elastic components (e.g. tendons and ligaments) but also the muscles that generate additional torque during movement. Although active (powered actuation) transtibial prostheses have the potential to bridge these gaps, the current control solutions limit their efficacy.

This thesis is focused on the development of a novel prosthetic control solution to address these needs. However, as dully noted by Thor Hanson in his book “Feathers: the Evolution of a Natural Miracle”: “In crafting his famous wings, Daedalus copied only the appearance of birds, ignoring the biological and physical processes that made their flight possible”. Thus, in order to emulate or substitute a certain function we need to go beyond appearance and comprehend its underlying principles. This is why the chapter will not only outline the dissertation and the problem, but also focus on the ankle complex and principles of locomotion to understand better the reason for and inspiration of the design decisions made throughout the project.

1.1 Research Hypothesis, Objectives, and Achievements and Outputs

The work in this thesis aims to address the long-term complications linked to continuous compensatory movements during a prolonged prosthesis use. The main hypothesis is that by including the user into the control loop of the prosthesis it will enable prosthetic behaviour closer to their natural gait, which in turn will reduce the amount of compensatory movements, hence a reduced wear and tear and long-term complications. Thus, the main objectives are: (1) creating an algorithm, which interprets user’s desired movement, serving as control contributions for the prosthetic movement; (2) hardware advancements, which enable wearability of the developed technology for data collection and real-time control; (3) creating and training a complete prosthetic controller, which incorporates the user input, provides the required stability, is integrated into a prosthetic device, and provides functionality across gait and non-gait activities; (4) use the developed prosthetic controller to test the hypothesis for compensatory movement reduction by comparing metrics of joint/lower back loading and energy consumption during prosthetic use controlled by the controller versus a passive prosthesis.

The thesis main contributions to improving the state of the art in prosthetic control are: (1) algorithm to obtain a novel neural signal for stiffness control from high-density electromyography (HDEMG); (2) biologically inspired hybrid control paradigm including a rhythmic automatic

component modulated by a neural component obtained at the muscle level; (3) novel universal and wearable HDEMG electrode design and interface for in-socket recordings at the lower limb; (4) publicly available sensor-rich data set for an extensive variety of locomotion activities. The major output of this thesis, which has been published in IEEE Transactions on Neural Systems and Rehabilitation Engineering, is the work in Chapter 2, although the data set work described in Chapter 4, as well as the work in chapters 3 and 5 are also aimed at journal publications.

1.2 Outline of Dissertation

In the remainder of Chapter 1, I will provide context for the underlying physiological principles that guided the signal processing and data acquisition and that served as an inspiration for the control approach. The physiology of the ankle complex, along with motor control principles and ankle joint stiffness modulation will be covered in Section 1.3. Following this, in Section 1.4, I will review the principles of locomotion, reflexes, and cortical involvement during vertebrate locomotion, that has been learned over decades of animal and human studies. Furthermore, I will go over the nature of surface electromyography (EMG) in Section 1.5 and the advances of lower limb prosthetic control in Section 1.6. I will conclude Chapter 1 reviewing lower limb amputation procedures and recent innovations that link to prosthetic control and sensory reinnervation in Section 1.7. From here onwards, any mention of EMG, including HDEMG, would refer to surface EMG, unless explicitly stated otherwise.

In Chapter 2 I will present the work done on the user input component of the control algorithm, demonstrating its design as well as the results achieved during its real-time use for control.

In Chapter 3 I provide details of the hardware and software developments, necessary for the actual implementation of a practical, fully wearable prosthetic control system involving HDEMG and an inertial measurement unit (IMU).

In Chapter 4 I will present the work done on the comprehensive data collection for the algorithm training, including brief results and technical validation of the collected data in comparison to other open-source databases.

In Chapter 5 I will present the automatic oscillatory component of the prosthetic controller and the final complete algorithm, combining the voluntary and automatic components, the approach used to combine them, additional rules and states, and the results with the trained controller, along with the full prosthetic integration with a two degrees-of-freedom (2 DoFs) active transtibial prosthesis.

In Chapter 6 I will provide concluding remarks, discuss potential future directions, and place this work in the broader research context.

1.3 The Ankle Complex

The ankle complex is comprised of multiple components (muscles, bones, tendons, etc.) working together towards shock absorption and support and propulsion of the body [20, 21, 22]. The movements provided by the ankle in each plane are plantarflexion/dorsiflexion (sagittal plane), inversion/eversion (frontal plane), and abduction/adduction (transverse plane). Combination of these also provides pronation and supination movements. This thesis is focused on the movements in the sagittal and frontal plane, and the information below is contextualized in terms of these movements, the muscles involved in these movements, and the ability to measure muscle activity using EMG.

1.3.1 Physiology

The ankle joint complex is comprised of three joints - the talocrural, the subtalar, and the talocalcaneonavicular joint (Figure 1.1). The talocrural joint is a synovial hinge type,

formed by the connection of the tibia, fibula, and talus. It is supported by ligaments connecting the tibia and fibula together as well

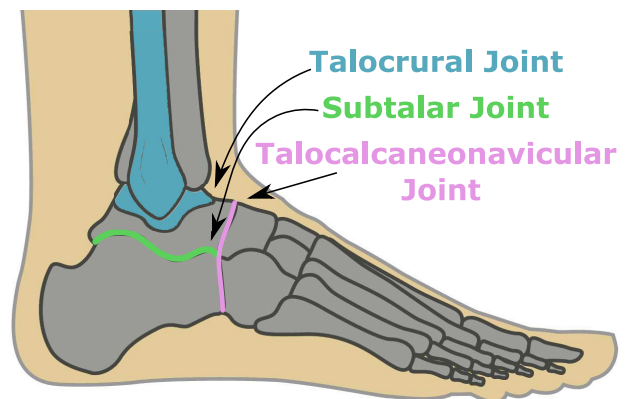


Figure 1.1: The ankle joint complex illustration.

as connecting each of them separately to the bones of the foot. This joint is mainly responsible for the dorsiflexion/plantarflexion movements of the foot provided by the muscle activity of the gastrocnemius lateralis (GL), gastrocnemius medialis (GM), soleus (SOL), and tibialis anterior (TA). The GL, GM, and SOL (all responsible for plantarflexion) are connected to the calcaneus bone via the Achilles tendon and are innervated by the tibial nerve. The TA (responsible for dorsiflexion) is connected to the foot via the anterior tibial tendon and is innervated by the deep peroneal nerve. In addition to the TA, there are three deep muscles that all together form the anterior muscle compartment of the foot - the extensor digitorum longus (EDL), extensor hallucis longus (EHL), and peroneus tertius (PT). The EHL and EDL are mainly responsible for the extension of the big toe and the other four smaller toes respectively, while the PT is responsible for eversion. All three are innervated by the deep fibular (peroneal) nerve and have a contribution towards dorsiflexion as well.

The subtalar joint is a plane synovial joint located at the articulation between the talus and the calcaneus. This joint is mainly responsible for the inversion/eversion of the foot provided by the TA, the tibialis posterior (TP), and the peroneal muscles. TA and TP are driving the foot's inversion while the peroneal muscles are driving the foot's eversion. TP and peroneal muscles are also contributing to plantarflexion. Peroneal muscles and TP are innervated by the superficial peroneal nerve and the tibial nerve respectively and are connected to the foot by their corresponding tendons. The flexor hallucis longus (FHL) and the flexor digitorum longus (FDL), similarly to TP, are also deep muscles innervated by the tibial nerve and are mainly responsible for the flexion of the big toe and the other four smaller toes respectively. They also have a contribution to inversion and plantarflexion of the foot but it is much smaller than that of the TP [23].

The TP and partially the SOL are the only deep muscles out of the aforementioned group with main contribution to the 2 DoFs of interest, which demonstrate that most of the muscles responsible for each of the 2 DoFs movements of the foot are accessible through EMG recordings. It also reveals a problem in separation between the dorsiflexion and inversion movement as there is only one superficial muscle (TA) that is responsible for both of the movements.

1.3.2 Function During Locomotion

The ankle provides shock absorption, support of the body in stance, and the majority of mechanical power in step-to-step transition [20, 21, 22] as well as 39%-47% of the total positive power during walking/running [24]. These functions relate to the physiology of the ankle joint, spanned by the long tendons of the muscle acting on it. These tendons provide the ankle with a spring-like properties by storing and returning elastic energy, with some energy loss due to viscoelastic effects, during locomotion [25]. On the other hand, the muscles connected via these tendons allow for motor- and damping-like properties by providing power generation [26, 27, 28] and energy absorption [29] when needed.

Furthermore, as walking is a mechanically unstable process and the foot provides the initial contact of the body with the environment during locomotion, the ankle has a major contribution towards providing the stability during locomotion. It has been suggested that this stability can be achieved by modulating joint stiffness rather than neural feedback [30, 31, 32]. Thus, understanding both the generation of movement and stiffness modulation during locomotion is necessary for the design of an intuitive myoelectric interface that seamlessly integrates with the rest of the human body. The ankle joint stiffness and modulation is further explored in the following subsection.

1.3.3 Ankle Joint Stiffness and Its Relationship to Muscle Activity

Joint impedance, expressed as the stiffness, damping, and inertia of the joint under dynamic conditions, has been suggested as the main mechanism for stabilizing otherwise unstable processes such as human locomotion [30, 31, 32]. Recent studies have shown that the variation of damping and inertial components of ankle impedance is not significant during walking [33, 34, 35]. Thus, part of the focus of the presented controller in this thesis is on a method for extracting a control signal for the stiffness component of the ankle joint. Joint stiffness is typically defined as the constant of proportionality that describes the relationship between displacement/angle and force/torque. The stiffness of the ankle joint is of major importance

during locomotion and its adjustment has been suggested as the mechanism that people use for changing speed and controlling downward and forward momentum during locomotion [36, 37].

Generally, the joint stiffness is comprised of three components: (1) passive, which is due to the stiffness properties of the tendon, joint, and connective tissue; (2) intrinsic, which is the stiffness contribution of muscle fibers without any neurological input; and (3) active, which is the contribution to joint stiffness of the voluntary and/or reflexive muscle contractions due to a neurological input. The initial attempts for estimating the joint stiffness were focused mainly on its passive and intrinsic components and included measuring intrinsic ankle stiffness in stance [38] as well as passive and intrinsic stiffness during locomotion [39]. However, these studies captured the joint stiffness only in stationary conditions and are not able to provide information on the stiffness in non-stationary ones (i.e. locomotion). Similarly, studies on quasi-stiffness, the derivative of the angle-torque relationship with respect to a set angle during performance tasks, are unable to capture the true dynamics of the joint stiffness. This is because the quasi-stiffness measurement disregards the energy-storage properties of the ankle [40] and has also been shown to vary greatly with walking speed and trajectory [41, 42]. This underscores the important need of perturbation during a performance tasks in order to capture the full dynamic stiffness. Recently, the combined work of Rose *et al.* [34] and Lee and Hogan [43] were able to capture such dynamic stiffness throughout the complete gait cycle during walking [33]. Another study by Ficanha *et al.* has provided and tested an additional procedure for the measurement of the dynamic ankle stiffness in 2 DoFs [44].

These studies are of utmost importance for the better understanding of the ankle joint dynamics and can provide guidance in the design of transtibial prostheses. However, they still lack information on joint stiffness modulation that happens outside cyclic gait motions, which, as aforementioned, has a major role in human stance and locomotion [31, 32, 41, 37]. These changes in stiffness are dictated by the nervous system in response to interactions with the physical environment and are usually modulated by muscle co-contraction [45, 46]. Muscles' stiffness properties have been shown to be force-dependent [47, 48], which stems from the fact that the number of actin-myosin cross-bridges increases with force during isometric contraction; thus, a larger number of cross-bridges translates to a higher stiffness. This also explains

how joint stiffness can be modulated independently from joint torque via increased agonist-antagonist contractions, resulting in greater stability of the joint during interactions with the environment. Further on that point, Morasso and Schieppati [49] highlight the requirement for an active mechanism of stiffness control during quiet standing, as passive muscle stiffness alone is insufficient to provide the observed stiffness changes during the activity. Back then, they postulated that the restabilization process rules out a purely reflexive mechanism and points towards a central process. One major limitation of their approach was the lack of accurate measurements of stiffness during balancing tasks, thus they couldn't completely validate their observations. However, such measurements exist nowadays and the stiffness values have been shown to fall under their assumption for the range of these values [50]. This is another area where a myoelectric interface can be important, as it can provide access to the muscle co-contraction.

1.4 Locomotion and principles of motor control

In order to build a control system that provides people with a natural control of their artificial foot it is necessary to understand not only the dynamics of the limb and its structural components, but also how is motor control, and specifically locomotion, implemented within the system. These principles of locomotion and motor control have served me as an inspiration for the prosthetic controller that I have developed and their understanding will provide useful background for the reason why certain choices were made during the controller's development.

Locomotion is one of the most fundamental and simultaneously most complex motor actions in all vertebrate organisms. It is much more than a propulsive mechanism, as it has to also provide adaptations for the movement, taking into account the goal of the animal and its surroundings based on decision making circuits and sensory information (e.g. vision, pressure, proprioception, etc.). Thus, the overall action is a result of multitude delicate interactions between intrinsic computations within a variety of neural circuits and the sensory input provided to them.

In terms of contributions of different parts of the nervous system towards movement control, Fig-

ure 1.2 provides a simplistic, yet quite informative overview of the motion control system organization. It illustrates how the basal ganglia, along with its cortical, thalamic, and dopamine system input, has a crucial role in decision making, representing the most complex level of the system. This activity is further passed through the brainstem, where it is organized into command lines to the specific spinal cord circuits, which in turn activate the skeletal muscles. The cerebellum also plays a vital part when it comes to motor learning and fine adjustment of movements.

Here, I would like to make a further clarification on why the rest of the chapter is going to refer to a variety of vertebrate animals from simplistic organisms such as the lamprey all the way to and including the human, although comparing these organisms might seem odd at first glance. The motor system is one of the most well-studied neural systems due to the access of vertebrate organisms that share similar structures between themselves. Because of the similarity of its organisation between vertebrate species, scientists were able to make observations that were transferable across vertebrates. The lamprey is one of the earliest (evolutionary speaking) and most simplistic species that still shares common motor infrastructure to primates (see Figure 1.3). Alongside it, the *Xenopus*, and zebrafish are two other simple animal model that together allowed researchers to truly characterize the motor circuit connectivity using dual recordings from

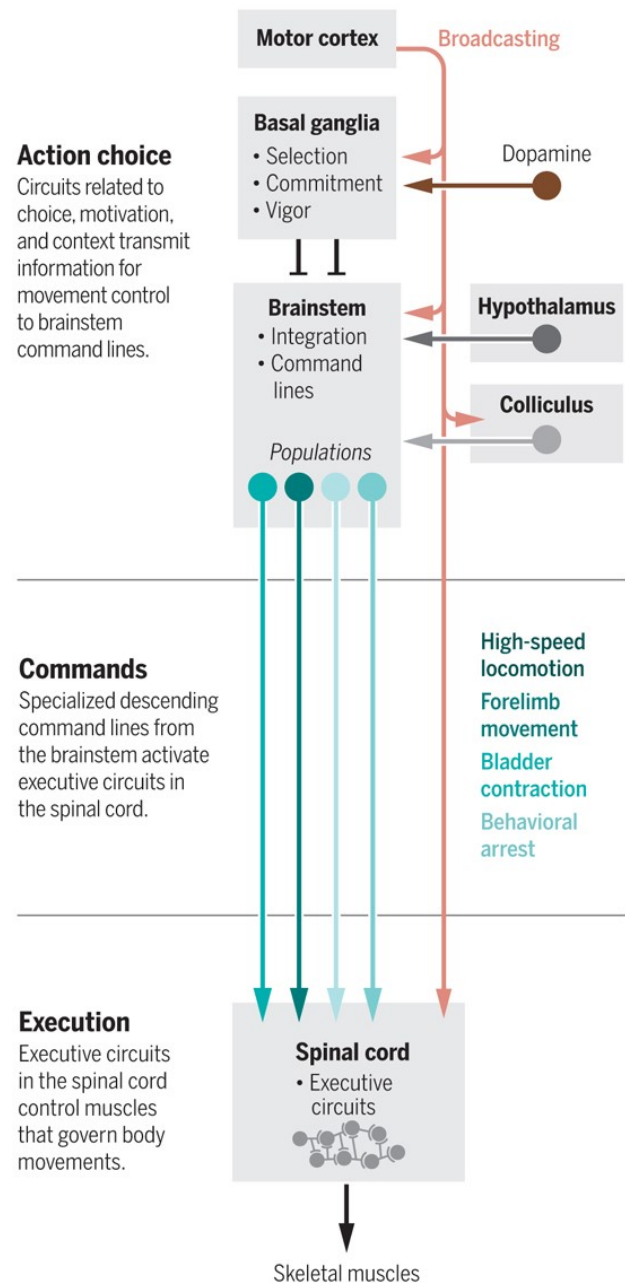


Figure 1.2: Movement control contributions of components of the nervous systems. [From Arber and Costa [51]].

the constituent neurons. Furthermore, because these animal models represent undulatory locomotion, access to more complex models is needed to study limb locomotion control, which includes mice, rats, and cats. Such animal models have also been studied extensively. Granted, their extensive circuit connectivity provides a big challenge that even the most modern neurophysiology tools struggle with. However, they have still provided incredibly valuable and much needed insights into how our motor system operates.

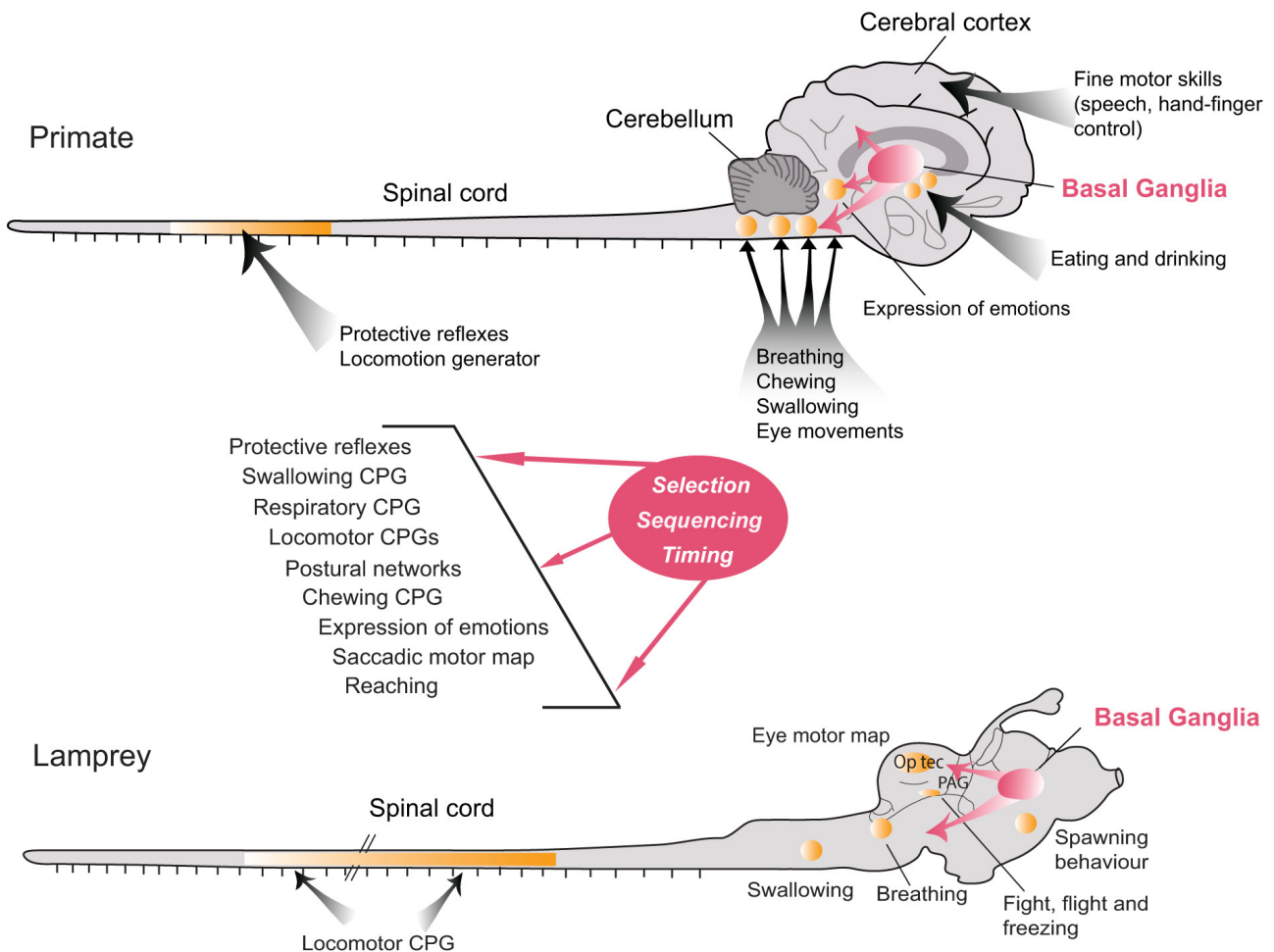


Figure 1.3: Illustration of commonality between the motor infrastructure of the lamprey and primate, containing all the key components of the system including spinal cord, brain stem, midbrain, and basal ganglia along with central pattern generator (CPG) circuits. [From Grillner and El Manira [52]]

A final note is in respect to early twentieth century remarks about human locomotion being a completely different class from other vertebrates due to the inability of babies to walk soon after they are born. However, a more recent study has offered an answer to why bipedal

human locomotion seems fundamentally different compared to other mammals when it comes to motor abilities after birth. Garwicz et al. [53] has demonstrated a linear correlation between the time, from conception (not birth), required for an animal to walk and the animal's brain weight. This suggests that there is an amount of brain development that needs to occur for the initiation of locomotion and the larger the brain is the longer it takes for the wiring and maturation of these circuits. Furthermore, Dominici et al. [54] also demonstrate a similar activation patterns in neonates across animal species, including humans, strengthening the similarity argument rather than contributing to the contrary. Thus, because of the significant motor circuit structural similarity and commonality of basic motor behavior between all of the aforementioned vertebrate animals and humans, we can assume that there is also a significant overlap of how the motor (and locomotion) elements of the nervous system are structured and wired, which is also demonstrated by studies that will be further referred to.

1.4.1 Locomotor System Components

As mentioned above, many systems take part in goal-oriented locomotion, spanning from the forebrain, through the spinal cord, and up to the muscle activating motor neurons themselves (Figure 1.4). Talking about goal-oriented movements, we cannot skip the visuomotor coordination that is needed to direct the movements along a certain path towards a particular target (food, shelter, evasion, etc.). It has been shown that the neurons in the optic tectum (superior colliculus in mammals) are directly involved in gaze reorientation and stimulus selection, potentially eliciting orientation towards a target or evasive maneuvers [55]. In mammals, mediation of the visuomotor coordination through the corticospinal system also enables precise placement and step cycle modification [56, 57] demonstrating its importance

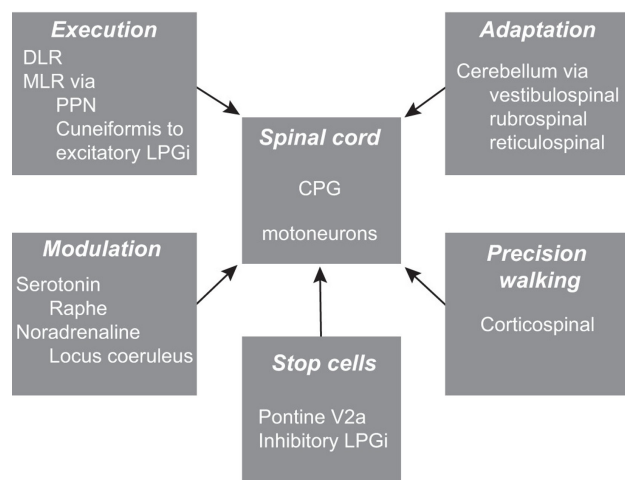


Figure 1.4: The different function of descending pathways converging onto the spinal cord CPGs modifying locomotion. [Adapted from Grillner and El Manira [52]]

during locomotion.

Of course, most people know about the motor cortex and its involvement in all motor functions, but another two critical areas when it comes to locomotion are the mes- and di- encephalon locomotor regions. The mesencephalon (MLR) and diencephalon (DLR), located in the midbrain, are the areas that control the activity in the spinal network via the brain stem reticulospinal systems [58, 59, 60]. In the mid-twentieth century scientists have shown that stimulating an area near the subthalamic nucleus in lightly anesthetized cats could elicit long-lasting walking movements [61, 62]. This was further corroborated by a later study in thalamic preparation cats, demonstrating varying locomotion activity (walk, trot, and gallop) controlled by stimulating the same area [63]. This area was later defined and now known as DLR, and has been shown to contain neurons projecting to the brain stem reticulospinal network. In this manner, they are activating spinal CPGs, while also having caudal projections towards the MLR region, suggesting possible parallel control exerted via MLR [64]. A pivotal discovery for the field of locomotion was made in the sixties, when Shik et al. demonstrated that stimulating the MLR area, elicits locomotion in decerebrate cat, modulating the walking speed depending on the strength of stimulation (low current initiates movements, with higher values inducing trot and then gallop) [65, 66]. This discovery meant that complex locomotor behaviour can be studied in animals without anesthesia. Furthermore, locomotion cessation has also been shown to be a result from a stimulation of MLR activating a reticulospinal subsystem [58, 67]. An important note to be made in respect to MLR and DLR is their modulation by the basal ganglia when it comes to determining a pattern of behaviour (i.e. locomotion initiation and cessation). Roseberry et al. [68] show in their study a direct pathway from the basal ganglia that activates glutamatergic neurons in MLR, leading also to locomotion initiation, as well as an indirect pathway onto the MLR that leads to reduction of locomotion activity. Furthermore, the substantia nigra, pars compacta (SNc), and the ventral tegmental area (VTA) (via their dopaminergic input as well as the histamine control) and the raphe nuclei (via their 5-hydroxytryptamine (5-HT) input) are also vital for the function of the basal ganglia. All of this, combined with the large involvement of the cerebellum in locomotion adaptation in response to short- and long-term perturbations (including phasic changes and error correction), demonstrates the vast

complexity of the locomotion system in the brain; and one of the most critical components, the spinal cord, has not been considered yet.

Spinal circuits possess the ability to integrate and transform non-patterned commands from the aforementioned brain areas into well-coordinated cyclical activity that produces locomotion. This patterned activity provides a precise muscle and limb coordination as well as speed and amplitude control of locomotor movements. The vital role of the spinal cord in locomotion is highlighted by the fact that locomotor movements, even after a high spinal transection, can be induced by sensory input in lamprey [69], dogfish [70], and *Xenopus* [71], or occur spontaneously in eel and dogfish [72, 73]. This demonstrates the capability of the spinal cord to generate coordinated locomotion movements by itself, lacking any supraspinal control, with EMG activity showing that the motor pattern is conserved [70]. Similar studies have been done in amphibians [74], reptiles [75], and mammals [76, 77, 78] showing again locomotion movement generation and speed control after a spinal lesion. Thus, this feature is conserved throughout vertebrate species. One of the big questions about mammalian locomotion in the past was whether locomotor activity is generated by CPGs or entirely depends on sensory information, with the former becoming the more likely answer as we've advanced our research. At the beginning of the 20th century, T. Graham Brown [79] was one of the first scientists to provide a strong evidence towards the central networks hypothesis in a decerebrated cat with transected dorsal roots and fully sectioned all nerves to the hindlimb muscles. In that study, he observed alternating rhythmic activity between the flexor (gastrocnemius) and extensor (tibialis anterior) muscles elicited in the complete absence of sensory feedback. There was an initial hypothesis following that discovery, suggesting a two half-centre model (for flexors and extensors) with reciprocal inhibition in-between. However, further evidence [80] was strongly in favour of proprioceptive feedback modifying the stereotypically produced flexor and extensor cycles, allowing for the complex adjustments seen during locomotion, which were unable to reproduce using a simpler half-centre hypothesis. As the research in the area progressed, more evidence was shown for complex pattern switching between flexors and extensors in the absence of proprioceptive reflexes [81, 82], and demonstrating CPGs' ability to generate initiation and termination of individual muscle activity for at the correct stage of the step cycle [83]. However,

while it is true that CPGs can generate rhythmic locomotor patterns by themselves, this should not be mistaken with the fact that sensory information is essential for the continuous adaptation of the pattern with ability to change the duration and intensity of muscle activity throughout the locomotion [84, 85, 86, 87].

1.4.2 Locomotion Control

The previous section described the neurological systems involved in locomotion, presenting evidence for their function. This section will explore further how these components interact with each other to achieve a stable and adaptable locomotion pattern. In its simplest form, locomotion is a cyclical activation of muscles constituting propulsive movement. It has been shown that spinal circuits (see above) can generate their own rhythmic pattern even in absence of any other input. However, how exactly is the coordination and cyclical activity produced or what input is needed for the initiation, cessation, and adaptation of these rhythmical patterns are the questions that will be explored here. Later on, I will employ this knowledge during the creation of my prosthetic control algorithm as an inspiration for its structure and function.

Locomotion Transition

In order to initiate locomotion, the animal would need to stand up first, implying the integration of muscle tone regulation for extensor muscles of the limb. Following this, it initiates the first step, replacing the extensor tone with bursts of flexor activity in successive limbs, generating alternating stepping movements. Conversely, the opposite occurs when transitioning from locomotion to standing. This indicates the need for coordination and interaction between the regulation of the muscle tone system and the locomotion one. It has been previously shown that two regions affect the muscle tone - the ventral and dorsal tegmentum [88, 89]. The former elicits standing up and consequent walking by increasing the extensor muscle tone, and the latter decreases it eliciting natural progression to lying down. The reticulospinal neurons mediate these effects by inhibiting both the motoneurons of hind- and forelimb via segmental inhibitory premotor interneurons [90].

Locomotion Initiation

Once standing, the locomotor circuits need to be activated to initiate locomotion. In lamprey, stimulation of MLR and DLR activates the reticulospinal neurons in the posterior (PRRN) and middle (MRRN) rhombencephalic nuclei that consequently excites the locomotor circuits in the spinal cord [91, 60, 92]. In cats and rodents, locomotion can be induced by stimulating the general area of the nucleus reticularis magnis (onto which the MLR is projecting) that has projections to the spinal cord or by administering cholinergic agonists locally [93]. Additionally, stimulation of the trigeminal nerve at the bulbar level [94] as well as within the fastigial nucleus or the caudal tectum near the midline [95] can also elicit locomotor activity, in all cases most likely mediated via reticulospinal neurons.

Locomotion Cessation

Terminating locomotion is naturally a smooth transition to standing rather than a total collapse of muscle tone one would observe if the locomotor drive is suddenly stopped. Recent findings shine the light on the mechanisms to initiate such transitions via activations in the brain stem. In lamprey, "stop cells" were discovered in the caudal part of MRRN after finding their bursting activity when a locomotion is ceased [67, 96]. Blocking the stop cells' activity allows for a gradual locomotion termination, while activating them leads to earlier stop. In mice, a gradual reduction of speed and termination of locomotion is elicited by activating a subgroup of reticulospinal neurons [97]. In addition, a separate mechanism for this was reported that involves inhibitory projection neurons of the lateral paragigantocellular nucleus onto the spinal cord, activation of which elicits similar response [58].

Locomotion Pattern Production and Adaptation

The ability, mentioned above, for the spinal cord CPGs to generate rhythmic activity even in the absence of sensory input was investigated even further in rodents and cats. These studies demonstrated that the activity is maintained even when different parts of the spinal

cord are separated from each other, with a tendency for a more stable rhythm in proximal muscle controlling segments [98, 99, 100, 101, 102]. This shows a distributed ability for rhythm generation, suggesting an organization of the spinal cord comprising of a set of circuits, each capable of generating burst activity, being coordinated via excitatory or inhibitory interactions. Thus, the flexibility to produce different walking directions (i.e. forward, backward, crouching, etc.) via the interaction between the different rhythmic circuits could be maintained in such structure. However, the question remains of how these rhythms are produced (globally vs locally) and how they are coordinated.

It has been previously established in *Xenopus* and lamprey that local excitatory interneurons mediate their basic rhythm [103, 104, 105]. These studies have further identified the neurons' connectivity with different components of the locomotion system, producing a framework for locomotion generation in vertebrates [103]. Similarly, researchers managed to identify that V2a interneurons are mediating the rhythm generation in zebrafish [106]. However, when researchers investigated organisms involving a limbed locomotion with much more complex networks like mice, then the results were unclear. Certain studies have looked into V2a [107, 108] and HB9 interneurons showing ability for rhythm generation, but further blocking these interneurons did not stop the drug-induced rhythm generation providing inconclusive results. Thus, it is still unclear in mice and larger animals of how locomotor rhythm is generated and the type of interneurons involved in that.

When it comes to coordinating the alternating patterns during locomotion, studies in lamprey show evidence for reciprocal inhibition of the left-right alternating coordination, discovering commissural interneurons as the mechanism ensuring the pattern's synchronicity [109, 110]. The same interneurons were identified also in *Xenopus* showing their direct connection to rhythm generating interneurons and how they mediate inhibition of other interneurons and motoneurons on the contralateral side of the spinal cord [111, 112]. Things become more complex when it comes to limbed locomotion, and studies in mice and cats look at the left-right coordination as well as the flexor-extensor one. During locomotion and scratching, interneurons have been found to be rhythmically active. These interneurons of classes V1 and V2b, providing ipsilateral inhibition, include Ia, Ib, and Renshaw interneurons. Silencing the V1 interneuron population

in vitro in mice prolongs the locomotor burst duration, thus slowing down the locomotion pattern [113], likely contributing to locomotor burst termination. Furthermore, silencing of both V1 and V2b interneurons synaptic transmission results in disruption of Ia reciprocal inhibition and flexor-extensor coordination [114, 115]. Regarding the left-right coordination, V0 interneurons were shown to turn the left-right alteration into synchronization. Moreover, this research demonstrated differences in coordination in the two subclasses of V0 interneurons based on speed. Excitatory V0d interneurons were identified to be responsible for coordination at high speed, while inhibitory V0d interneurons were responsible for the one slower speeds. One must also not forget that some of these interneurons (V0v and V2a in particular) have long projecting neurons [116], underlining the importance of such in the coordination along the body.

Lastly, these locomotor patterns, although stereotypical, are also being modulated by sensory input from afferents. Studies in tetrapods have provided information about the importance of feedback for load and position during locomotion. In particular, step cycle regulation has been shown to be heavily influenced by hip position afferents [85], the information of which is also transmitted to the cerebellum [117]. Furthermore, hip position also has a major role during stance and swing transitions - if the limb's posterior angle at which it typically switches from stance to swing is delayed, then the transition is delayed and vice versa. Similarly for touch down - if the limb's forward movement during the swing phase is faster, the flexor activity would be shorter and, if it is hampered during movement, the flexor activity will be prolonged [118, 119, 120].

Load information, coming mostly from the Golgi tendon organ afferents (1b), also contributes to locomotion cycle dynamics. This is clearly illustrated by the fact that a transition into swing tends to be initiated by a decrease in load and, conversely, a load increase tends to maintain the extensor activity [121, 122, 84]. Stimulation experiments have shown that activating ankle and knee extensors 1b afferents during extension facilitates the extension phase and activating them during the flexion phase terminates rapidly the flexion and activates the extension, pointing out that the modulation of the synaptic response happens within the step cycle [123, 124, 125]. Muscle spindles afferents (1a/II) and cutaneous receptors have also been shown to affect the

locomotion pattern. Muscle spindles seem to prolong ankle flexion in mice with eliminated muscle spindle afferents only (cutaneous, joint, and 1b afferents left untouched) [126]. The 1a/II afferents have further been shown to increase extensors' activity (especially ankle) when stimulated [86]. Other studies have shown that cutaneous receptor input is critical for foot placement during locomotion and precision walking [127, 128, 129].

Another area of modulation, which the sensory input provides, is in phase-dependent reflex reversal. This is a component present in vertebrates (lampreys to mammals) and invertebrates and likely a general locomotor system feature [130]. Encountering an obstacle during swing, the foot will adapt its movement by increasing flexion to overcome the obstacle, but if the same obstacle impedes the foot's movement during the support phase that will increase the foot's extension. This has been seen both in rodents and cats and has been demonstrated as a result from a sensory input by eliciting the same response by stimulating (by touch) the hairy skin on the dorsum of the foot [131, 86]. Similarly, hip position is also able to gate a reflex. Peripheral nerve stimulation, which elicits movements, will induce extension if the limb is flexed, and flexion if the limb is extended [85]. Such position-dependent gating is likely to play a role for changing the effects of supraspinal signals as well [132].

All these aforementioned changes within the locomotion pattern demonstrate that the final locomotor movement is the result not only of the CPG activity but also of its modulation from the sensory afferents.

Locomotion Changes and Fine-tuning

Whether it will be for steering, body orientation, or adaptation to perturbations, other brain areas are also tightly involved in the locomotion system. Areas such as the midbrain tectum, cerebellum, and the vestibular system play a large role in "fine-tuning" the locomotion and initiating changes in response to external stimuli. It is well-known that the vestibular apparatus provides rich information for head movement. In lower vertebrate organisms with undulated movement, such as the lamprey, tilting of the head during swimming increases activity of the reticulospinal neurons on the contralateral side. This, in turn, will act upon spinal motoneu-

rons, counteracting the movement. [133, 134]. In higher vertebrates, such as cats, rodents, and rabbits, such asymmetric activation in the vestibular system results in postural changes during standing and locomotion [135, 136, 137, 138]. For example, lateral perturbations during locomotion result in adduction or abduction of the respective limbs for the next swing phase in order to stabilize the following support phase [139, 140].

Another area for changes during locomotion is the superior colliculus (midbrain tectum), which is involved in steering. It receives information about the surrounding space as a retinoscopic map formed by eye afferents [141, 142] to produce orientating and evasive movements [143, 144, 145, 146]. Research in dogfish shows that stimulating the tectum area results in body curvature and fins angle changes during locomotion, promoting turning [147]. The same thing happens in cats during walking, when the body curvature and limbs rotation angle change in response to tectum stimulation, inducing turning movement [148]. In rodents, since the superior colliculus plays a larger role in orienting movements than the visual cortex [149], stimulating it results in orienting or evasive movements [143].

Lastly, the cerebellum is another area involved heavily in locomotion adaptation due to perturbations. Its main source of information is the efferent copy of the movement that it receives from the spinal cord via the spinocerebellar and spino-reticulo-cerebellar pathways [150, 151]. This input phasically entrains the Purkinje cells in the cerebellum and the reticulo- and rubrospinal neurons, which directly and indirectly drive the extension during extension phase (Purkinje cells) or flexion during flexion phase (reticulo- and rubrospinal neurons) [152, 153, 154]. Further evidence for this has been provided by the observation that movement modification and hyperflexion occur if the anterior cerebellar lobe is inactivated [155, 156]. Cerebellum is also involved in locomotion learning, which has been demonstrated in tests with split-belt treadmill using different speeds for each belts. Observation during these experiments show early adaptations expressed in shortening of the support phase of the limb on the fast belt and prolonging it for the limb on the slow belt, which are most likely due to spinal mechanisms [157, 158]. However, more complex spatial and temporal adaptations are developed over multiple trials and are dependent on the cerebellum [159].

Ultimately, all this evidence illustrates that there is a continuous monitoring and, if needed, adaptation of the locomotor movements by the cerebellum. Most likely, especially during fast movements due to inherent time delays, the ongoing movement cannot be fully corrected and the appropriate corrections are rather provided to the subsequent step.

1.5 Surface Electromyography

On the end effector side of things, these highly complex signals, processed by the central nervous system and outputted by the spinal cord, eventually innervate their respective muscle fibres. These efferent neurons, coming out of the spinal cord and innervating muscle fibres are called motor neurons. A single motor neuron innervates multiple muscle fibers and together they form a motor unit. The "neural drive" represents the action potentials sent by the motor unit and the "muscle activation" represents the action potentials generated by the muscle fibers. The electromyogram (EMG) is the recording of these "muscle activations", which can be done either non-invasively, through surface EMG, or invasively, through intramuscular EMG (iEMG). In general, this activity reflects the force generated by the muscle fibers. However, the relationship between the activity picked up by the EMG and the muscle force is not direct [160], as it is characterized by the non-linear relationship between muscle's length, shortening velocity, and level of fatigue [161, 162, 163, 164].

As mentioned, the EMG can be recorded intramuscularly or on the surface of the muscle. While the latter has disadvantages in terms of resolution of information and skin artifacts, it is still preferred for myoelectric control due to its non-invasive nature and its advantage for collecting functional motor data. Surface EMG recordings can be done via single electrodes (usually placed at the belly of the recorded muscle) or electrode grids (applied above the muscle). If the electrodes in a grid are closely spaced then the recording from it is referred to as high-density EMG (HDEMG). In comparison to single electrode surface EMG, which samples the signal from the whole muscle, HDEMG provides a spacial information about distribution of electric potential over the recorded area and its evolution in time. This can be expressed as 2D image

maps or sequences.

Currently, commercially available myoelectric upper limb prostheses do not employ any HDEMG in their interface, although efforts have been made in that direction. [165, 166]. Furthermore, the electrodes could be positioned in a monopolar or bipolar arrangement. The monopolar arrangement involves the use of a single recording electrode and a reference electrode, while bipolar includes two recording electrodes and a third reference one. While the bipolar arrangement has an advantage for the elimination of electromagnetic noise, its disadvantage is the elimination of some of the EMG signal along with the electromagnetic noise that is the result of the common mode rejection [167]. In contrast, although the monopolar arrangement is sensitive to electromagnetic noise, it preserves all the information contained in the EMG [168].

1.6 Lower Limb Prosthetic Hardware and Control

Generally, passively driven ankle prosthesis involve either a solid ankle cushioned heel (SACH) or an energy storage and return (ESAR) mechanism. ESAR provides a major energy expenditure improvement over SACH prosthesis [170, 171] due to the spring properties of the carbon fiber used for their manufacturing. These spring properties provide additional force during the push-off phase, thus the user has to exert less energy while walking. A consecutive milestone in prosthetic hardware development are the semi-active prostheses, which involve using rheology or valve systems (mostly for the knee joint) allowing variable damping in addition

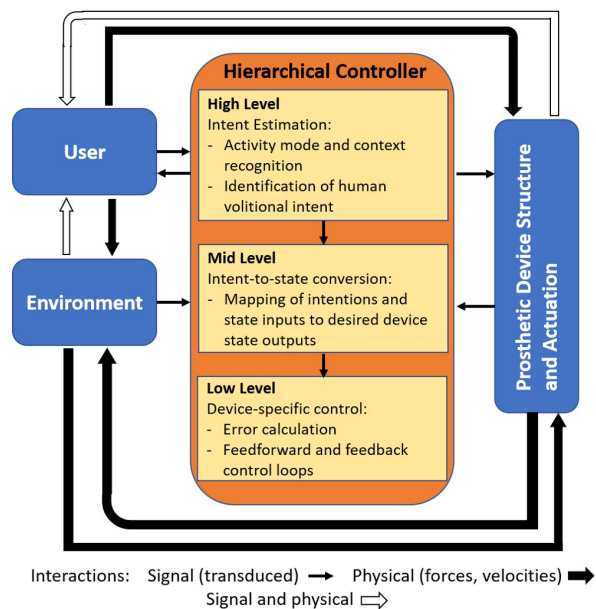


Figure 1.5: General control framework for active lower limb prosthetics. Arrows indicate exchange of information between the blocks. Adapted from Tucker *et al.* 2015 [169].

to variable stiffness. Their impedance is usually pre-set using stiffness and damping constants, but they still cannot match normal energy requirements for tasks such as climbing stairs or steep slopes. Energetically, active lower limb prostheses, as mentioned before, are currently the only ones capable of restoring the functionality of the lower-limb in terms of energy expenditure, obstacle avoidance and volitional control. This enables the restoration of gait patterns across different terrains and activities similar to those of able-bodied people [172]. This can reduce/eliminate current medical complications due to abnormal gait patterns and also potentially alleviate phantom limb pain [173]. However, such energetically active prostheses require control of their actuation, which, if inadequate, can result in incidents caused or exacerbated by inappropriate actuation of the prosthesis. This is why reliable and robust prosthetic control in such devices is a critical component.

Currently, the trend in lower-limb prosthetic control is towards a hierarchical controller, the general concept of which is presented in Figure 1.5. The high level component of the controller is responsible for the detection of user's intent, which is passed down to the mid level that translates that intent into states for the low level. There, these states are converted into specific commands for the prosthesis (i.e. impedance, position, torque). The high level typically comprises a heuristic rule-based classifier like a finite state machine [174, 175] or a decision tree [176, 177] that determines the activity (gait mode). Both of these popular classifiers work on a similar basis, where the classifier receives an input from the sensors of the prosthesis and, based on a fixed set of rules for gait mode transition, determines the current gait mode (out of a pre-defined set of modes). An alternative for activity recognition is a machine learning approach, which avoids the heuristic nature of the previous classifiers. In such a machine learning approach, the decision boundaries determining the gait mode are generated automatically (no heuristic input) based on a training data for set gait modes. This can be achieved through a plethora of pattern recognition algorithms with varying success. However, this approach also has its drawbacks, mainly in terms of training data collection and generalization and transparency of the algorithm. The training data that needs to be collected and fed to such a classifier has to include all the activities and the transition between each of them, which can be a lengthy process and is not always possible. Furthermore, the decision boundaries generated

for one person might greatly differ from those of another one and their (decision boundaries) connection to real-life conditions of the prosthesis might not be easily interpretable.

Following the determination of activity at the high level in the aforementioned framework, the command is sent to the mid level, where it is translated into a desired state for the prosthesis that will be tracked by the low level component of the controller. Typically, there are multiple control laws at the mid level that can be either dependent on the gait phase (phase-based) or independent of it (non-phase-based). Phase-based rules rely upon identification of a certain gait phase(s) (gait phases illustrated in Figure 1.6), like heel strike or toe-off, to guide the prosthesis behaviour within gait cycles. There are many approaches towards constructing control laws at this stage such as: setting invariant [178] or normalized movement trajectories [179] that are specific between certain gait events; echo control scheme that replays delayed movements of the non-amputated leg [180]; actuating the device during swing based on virtual constraints using the centre of pressure as a phase variable [178]; or determining the position and/or the impedance at each gate phase using finite-state controllers (FSCs) [181, 182, 183]. All of these methods have advantages and disadvantages but the most implemented by far is the FSCs approach [169]. The main drawback of phase-based rules is that they don't allow any changes to the prosthesis within a gait phase, which can be avoided by using non-phase-based rules. A prime example of this is the complementary limb motion estimation (CLME), which, similarly to echo control, uses movements of the residual limbs to determine the trajectory that the prosthesis has to follow. However, it is fundamentally different from echo control because instead of using just the movements of the non-amputated leg and replaying them with a delay, it uses movements of other body parts as well, has no delay, and is not just replicating a set motion but maps the movements to a predefined trajectory associated with them. This method has been successfully implemented for generating kinematics (for level-ground walking and stair ambulation) [184] as well as stiffness (only for level-ground walking) [185]. However, as this method relies on a set of generated general trajectories, more evaluation is still needed to determine the degree of generalization across people and activities that can be achieved.

The desired state determined by the mid level component of the controller is passed to the low level controller, which calculates the error between the current and the desired state of the prosthesis and sends commands to the actuator(s) to reduce it. The desired state that is typically tracked and controlled is either the joint's position, impedance, velocity, torque, or admittance (inverse of impedance) but a potential control of a combination of states (i.e. position and impedance) is also possible. Depending on the specific prosthetic device, the low level can implement a feedforward loop, feedback loop or a combination of both in order to achieve the desired state.

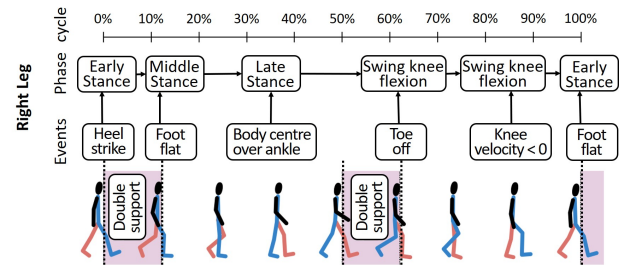


Figure 1.6: Illustration of gait phases during locomotion. Adapted from Tucker *et al.* 2015 [169].

1.6.1 Current State of Active Transtibial Prosthetic Hardware

When it comes to commercial availability, there is only one actively powered transtibial prosthesis (Empower, Ottobock) on the market [186]. However, there have been many research solutions that have been explored, with the hopes of improving the state of the art and commercialising such products. In fact, the Empower prosthesis mentioned above, came from such research development efforts at MIT. It is a 1-DoF active prosthesis, which is torque-controlled during stance by a reflex-based algorithm, developed by Geyer and Herr [187], and position-controlled during swing by setting the position to a constant for the gait phase. The prosthesis uses a rotary Series-Elastic Actuator, comprising of a DC motor along with a transmission in series with a spring, to provide force control by modulating the series spring compression [188]. It relies on Hall-effect angle sensor for position and strain gauges for ankle joint torque feedback for the low-level command error computation. However, the algorithm itself uses this sensor data to segment the stance phase into three distinct parts and to switch between stance and swing phase controller. The total weight of the prosthesis is 2145 g (for the 27cm height model) and the maximum allowable user weight is 130kg. The range of motions specified by

the manufacturer is 22° of plantarflexion and a dorsiflexion angle dependent on the carbon foot (not further specified). Another example of an actively powered transtibial prosthesis is the one developed in the Vanderbilt Transtibial Prosthesis [183]. It consists of a Maxon EC30 4-pole brushless motor along with a 143:1 transmission ratio, generating approximately 70 Nm of maximum torque, used in a conjunction with a spring in parallel in an open-loop torque compensation configuration. The range of motion achieved with it is 25° of plantarflexion and 45° of dorsiflexion, with an overall prosthetic weight of 2.3 kg. It uses a six-axis IMU and a magnetic absolute position sensor to subdivide the gait cycle into specific phases, each of which associates with a fixed set of parameters for an overall impedance equation. This impedance equation is used to determine the torque of the prosthesis. Later iterations of this work include using the IMU data to calculate shank angle and incorporate that for modifying the push-off gait phase threshold and mid-stance and push-off impedance to improve uneven terrain gait [189, 190]. There are also prostheses that use a pure motor-driven actuation without the assistance of an additional spring. A recent example of that is the PKU-RoboTPro developed at the Pekin University [191, 192]. It uses a 50W DC motor (Maxon EC45) to drive the carbon fibre foot through a gear box linked to three-bar linkage mechanism that actuates the carbon foot at the heel. The prosthesis uses a strain gauge to detect gait events and modes (stand, sit, and walk), an angle sensor at the ankle joint and two six-axis IMUs (at the foot and shank) utilized for the calculation of the overall damping and position control for the stance and swing phases respectively. It achieves 25° of plantarflexion and 25° of dorsiflexion with an overall weight of 1.75kg (without a battery), although a total weight is not specified, which makes it harder to compare to the rest. A notable progress has to be made when it comes to open-source hardware as well. Although not commercially available, the Open-source Leg (OSL) developed at the University of Michigan is available for purchasing for research purposes [193]. As an open-source projects, all the components are listed and the assembly procedure is well described, thus the whole system can be build from scratch by a researcher paying only for the source materials. The transtibial version weighs 1740 g and has a 20° of plantarflexion and 10° of dorsiflexion (the ratio between plantar- and dorsiflexion can be modified). In terms of actuation, it uses a similar approach to the PKU-RoboTPro prosthesis, with different actuation, gearbox, and

transmission designs, achieving peak torque (20 sec) of 148 Nm (± 41 Nm). There are a few default options that are available for the prosthetic control, based on an impedance modulation scheme (using sensing from the six-axis IMU, the embedded strain gauge, and the ankle joint angle sensor), but it also allows for custom control schemes that can be implemented by the researcher.

All of the aforementioned prosthetic hardware pertains to 1-DoF fully-powered actuation as the 2-DoF ones are more scarce. The prosthetic characterisation of the recently developed 2-DoF prosthesis by the group of Prof Hugh Herr at MIT [194] is still not publicly available, with the only other self-contained fully actuated 2-DoF prosthesis publicly characterised being the one by Jang *et al.* developed at the Korea University of Technology and Education [195]. It weighs 2250 g, offers 30° of plantarflexion, 30° of dorsiflexion, 20° of inversion and 20° of eversion, and can generate maximum 250 Nm of sagittal and 152 Nm of frontal plane torque. The actuation mechanism uses two unidirectional parallel elastic actuators (UPEA). This prosthesis uses an impedance control scheme with pre-set target coefficients for each of four sub-divided gait phases and utilizes the ankle angle (provided by a hall sensor) and velocity (provided by an IMU sensor) to calculate the output error.

1.6.2 Use of sEMG for Lower Limb Prosthetic Control

Regardless of the choices for the different components of the hierarchical controller, a neural interface can be implemented within its structure. This can serve to improve the activity recognition performance as well as modulate the prosthesis behavior (desired state) based on the user's intent. This can be achieved via a myoelectric interface like EMG, which is preferred due to its non-invasive nature and the breadth of studies conducted with it. Additionally, it has a timing advantage compared to mechanical sensors due to the electromechanical delay between motor commands and force generated by the muscles, which results in tens of milliseconds difference between the command and the action [196, 197]. Activity recognition through EMG signals is based on the association of patterns of muscle activity with a set of gait modes. Such EMG approach in lower-limb prostheses has been shown to perform on par with inertial sensors

and better than kinetics and kinematics sensors [198] as well as to offer notable advantages in terms of delays and performance during stair descent ambulation and transition [199, 188]. Furthermore, a hybrid approach for activity recognition combining both EMG and mechanical sensors has demonstrated clear improvements in both gait mode classification and error during transitions between activities [198, 200, 201].

Another use of EMG in prosthetic control is to modulate the prosthesis state during an activity. As mentioned above, a desired state in the presented generalized control framework is determined by the mid level component of the controller, which usually employs FSCs for the different gait phases. Each of the FSCs are guided by sensors to determine the desired state (i.e. torque, position, impedance). It has been previously shown that EMG sensors can be used to compliment mechanical sensors for the determination of desired states [202]. There can be three approaches towards this goal: (1) a direct approach, where the device state (i.e. torque) is directly modulated by the muscle activity detected by EMG; (2) a model-based approach, where a neuromusculoskeletal model that includes an input(s) from EMG is used to determine the device state (i.e. torque); (3) or a machine learning approach where the EMG is mapped to a desired state (i.e. position). The direct approach is not usually used for prosthetic control as it has been found to be too unstable by itself, thus the EMG signal is typically implemented in a model. The EMG input to such a model can be either just the processed EMG signal or a mapped signal (through machine learning algorithms) that represents the relationship between the EMG signal and the associated state (i.e. position, stiffness).

Processed EMG signals have been implemented in neuromusculoskeletal models to control knee flexion/extension virtually [203] or during a stair ascent activity [204]. This approach has also been used in transtibial prostheses for torque modulation of plantarflexion during stair ambulation [202]. A machine learning based approach has also been implemented for the virtual control of up to 3 DoFs of the ankle [205] and 4 DoFs of the leg (2 DoFs of the ankle and 2 DoFs of the knee) [206] although these were only classification tasks for movements involving the associated DoFs. This is an important distinction as the discretization level that could be achieved by classification (number of distinct movements) is not sufficient to capture the continuous natural movements of the limb. Furthermore, the sequential nature of this method

doesn't allow for more than one specific movement at a time. This underscores the better suitability of a regression type method for the control of leg motions.

1.6.3 Other Sensing Modalities for Prosthetic Control

In general, we can separate the sensing modalities into physical, physiological, and neural. The sEMG approaches described above pertain to the neural sensing modalities. However, other sensing modalities have also been used either in conjunction with neural signals or in isolation to obtain parameters used for a prosthetic control algorithm. One of the most widely used physical sensing modalities is an IMU sensor. IMU is a general term used to describe a combination of sensors (accelerometers, gyroscopes, and magnetometers) that are used to measure linear acceleration, angular velocity, and can also obtain an estimate for 3D orientation of the IMU. When people specify a 6-axis IMU, they refer to a combination of a 3-axis accelerometer and a 3-axis gyroscope, and when they specify a 9-axis IMU (sometimes referred to as magnetic and inertial measurement unit) it includes an extra 3-axis magnetometer sensor. If a magnetometer is available and reliable magnetic signal can be obtained, data fusion algorithms can be used to provide a 3D orientation estimate. Typically, magnetometers are not utilized in prosthetic control since the sensor is closed to a metal body (prosthesis connector, pylon) and/or copper coils (in the case of brushless motor actuators), preventing a reliable magnetic signal reading. IMUs have been used in prosthetic control to determine gait (i.e. speed, gait phase) [207, 208] or control parameters (i.e. impedance equation coefficients) [209]. Other approaches utilize the IMU signals for switching between control states or locomotion modes in a finite state control approach [210, 22]. Other physical sensors, like potentiometers, strain gauges, force sensors, and goniometers, have also been applied in a similar way for determination of joint angles [211], torques [181], or locomotion modes/control states [212].

Physiological signals, such as mechanomyography (measuring muscle sounds), sonomyography (measuring muscle thickness) and ultrasound (measuring muscle deformation), have also been explored as promising modalities to characterize muscle behaviour and use this information for prosthetic control [213, 214, 215]. Likewise, other non-muscle-related physiological signals,

including metabolic cost, breathing frequency, and heart rate, have been used as a feedback parameter for optimization targets of human-in-the-loop prosthetic/robotic devices [216, 217, 218].

This thesis employs mainly sEMG and IMU signals for inputs of the prosthetic controller. The necessity of sEMG signal was deemed on the basis of a need for direct signal of human movement intention detected as a resulting electrical activity in the muscles. The reason for not utilizing other modalities to achieve that, such as the aforementioned mechanomyography, sonomyography, or ultrasound, was because of the maturity of EMG as sensing modality, its direct relationship to neurological input, and its ease of embedding into a wearable microprocessor prosthetic system. The IMU was chosen as a mechanical sensor as it provides a very useful information, namely linear and angular accelerations of the body, at a very low cost and high availability at the prosthesis level. IMUs are available on every prosthetic device and, recording it in isolation provides the same data as obtaining this signal from a prosthetic-embedded sensor. For example, as long as the sensor model is the same, shank segment accelerations will be the same whether they are recorded from an embedded device or a sensor on top of the prosthesis once a correction is applied for a difference in placement. This is different from in-socket recording sensors, such as EMG, mechanomyography, or pressure sensing, since recording those signals from able-bodied individuals does not contain information about the contact that occurs between the limb and the socket during movements, which also introduces artifacts and non-linearities to the signal. However, further work can explore other sensing modalities that are also often included within a prosthetic hardware.

1.7 Amputation Procedures

Surgical procedures, in addition to the innate differences in muscle physiology and movement coordination of humans, cause amputee-specific physiological differences in the residual muscles of amputees, affecting their ability to control the muscles. This is due to the varying extent of peripheral damage that influences both muscle mechanics and sensory pathways [219]. Some of

these amputee-specific physiological differences, such as muscle length and tone of the residual muscles, represent permanently fixed attributes changed by the amount of sensory feedback pathway damage caused by the amputation procedure [220]. Furthermore, the damage to the residual muscle tissue affects the muscle contraction characteristics, which are influenced by the muscle tone. This is because the damage changes the muscle fibers' viscoelastic properties, which along with the active contractile properties determine the muscle tone [221]. This is why it is important to advance not only the prosthetic technologies but also the amputation procedures.

In the past decade, there have been a few major advancements in surgical procedures that affect the outcome of prosthetic integration and control - targeted muscle reinnervation (TMR), regenerative peripheral nerve interface (RPNI), and agonist-antagonist myoneural interface (AMI). TMR and RPNI have the same aim, namely, to connect nerves severed during the procedure to muscles in order to reinnervate them. This is an attempt to help with neuromas as well as for the muscles to act as biological amplifiers to improve the potential interface between the amputee and the prosthesis. TMR achieves that by connecting residual nerves to superficial muscles proximal to the amputation site [222], while RPNI reinnervates the residual nerves to cultured myoblasts implanted proximal to the amputation site [223]. The improvement that AMI aims to achieve is to restore the agonist-antagonist muscle interaction enabling natural proprioception [224, 225]. It attempts that by surgically connecting residual nerves to subdermally implanted pair of muscle grafts connected in an agonist-antagonist relationship [226]. While initial work was mostly done on rats, a new case study with an AMI subject has showcased its potential for prosthetic control [194]. There are also ample examples of improved prosthetic control due to TMR [227, 228, 229, 230, 231], as well as promising results for the treatment of post-operational neuroma due to TMR [232].

1.8 Summary

In this chapter, necessary background information was introduced, which will be used to define targets for and develop the structure of a transtibial prosthesis controller, the main aim of the thesis. Section 1.3 introduces the ankle complex, which demonstrates the main functions that the prosthesis has to emulate and why they are important for restoring movement abilities for people with below-knee amputations. Specifically, why it is imperative to include motion in the frontal plane and stiffness modulation of the ankle joint when providing a substitute for the foot. Section 1.4 provides the main principles of locomotion that served as an inspiration when creating this algorithm. It illustrates how vertebrate locomotion, in its most basic form, involves a system (spinal cord) that provides a variety of oscillatory activations to the limbs, and another one (brain and peripheral sensory input) that modifies, inhibits, or facilitates these oscillations [52, 129]. Furthermore, due to the delays in the nervous system, fast responses to perturbations are provided by reflex mechanisms, which can correct the movement in response to the environment without undergoing higher level of reasoning and decision making. This information motivated the structure of the prosthetic controller presented in Chapter 5. Later on, I will elaborate how the controller's structures include an automatic component, providing adaptive oscillators, which are modulated by the neural input provided from the user, gated by a simple phase reset reflex to provide fast modulation in case the foot is perturbed by an obstacle. Moreover, Sections 1.5 and 1.6 introduce the techniques used for obtaining muscle signals and current developments of prosthetic controllers to underline the novelty of this thesis and what distinguishes it from current approaches. Namely, the ability for continuous modulation of 2 DoFs and joint stiffness, combined with a holistic approach allowing for both modulation during locomotion and free space movements. Section 1.7 of this chapter highlights the variability of the residual limb's physiology based on the surgical procedure performed, demonstrating not only novel amputation procedures but also the importance of having a controller that is able to generalize between this variation of strategies for limb amputations. The following Chapter 2 will introduce the development and testing of the approach for providing user input, for modulating prosthetic behaviour, implemented in the final algorithm.

Chapter 2

Ankle Position and Stiffness Predictions from HDEMG

Following on from the literature review, this thesis work started with devising a solution for extracting the user input component of the eventual prosthetic controller using the information from high density electromyography (HDEMG). In isolation, this chapter's output is an algorithm that relies solely on muscle signals for user-desired position and stiffness of the foot in 2 DoFs. However, in the broader context of the thesis, it serves as an input for the overall prosthetic controller and represents the human voluntary input that is integrated along with rhythmic patterns and IMU sensing information for the final output. The chapter below corresponds exactly to a peer-reviewed manuscript [233], published under the title Real-Time Interface Algorithm for Ankle Kinematics and Stiffness from Electromyographic Signals.

2.1 Abstract

Shortcomings in capabilities of below-knee (transtibial) prostheses, compared to their biological counterparts, still cause medical complications and functional deficit to millions of amputees around the world. Although active (powered actuation) transtibial prostheses have the potential to bridge these gaps, the current control solutions limit their efficacy. Here we describe the

development of a novel interface for two degrees-of-freedom position and stiffness control for below-knee amputees. The developed algorithm for the interface relies entirely on muscle electrical signals from the lower leg. The algorithm was tested for voluntary position and stiffness control in eight able-bodied and two transtibial amputees and for voluntary stiffness control with foot position estimation while walking in eight able-bodied and one transtibial amputee. The results of the voluntary control experiment demonstrated a promising target reaching success rate, higher for amputees compared to the able-bodied individuals (82.5% and 72.5% compared to 72.5% and 68.1% for the position and position and stiffness matching tasks respectively). Further, the algorithm could provide the means to control four stiffness levels during walking in both amputee and able-bodied individuals while providing estimates of foot kinematics (gait cycle cross-correlation $>75\%$ for the sagittal and $>90\%$ for the frontal plane and gait cycle root mean square error $<7.5^\circ$ in sagittal and $<3^\circ$ in frontal plane for able-bodied and amputee individuals across three walking speeds). The results from the two experiments demonstrate the feasibility of using this novel algorithm for online control of multiple degrees of freedom and of their stiffness in lower limb prostheses.

2.2 Introduction

Below-knee (transtibial) amputation poses significant challenges for the locomotion of the millions of amputees worldwide [234]. Most of these people are fitted with a passive prosthesis in an attempt to substitute the missing limb. The limited energy generation capabilities of these prostheses [235, 18, 19] and their inability for active adjustment of foot kinematics and ankle joint properties during locomotion are in stark contrast to their biological counterparts. As a result, gait asymmetry [236, 237, 238] and increased loading on the contralateral limb joints [239, 240] and lower back [241, 242] occur. These compensations can cause further medical complications such as knee/hip pain [243, 12], back pain [244, 181], and osteoarthritis [243, 15]. Active transtibial prostheses (possessing power generating capabilities) could potentially address the issues of discrepancies in power requirements and adjustments of ankle kinematics and joint properties. A few such devices have been developed over the past years, resolving

most of the mechanical challenges that they pose [245, 246, 191, 247, 248, 249]. During comparative tests with passive prostheses, the active ones have shown benefits in terms of reduced metabolic cost [250, 22] and unaffected leg's peak ground reaction force (GRF) [251], as well as increased positive and net ankle work [22, 252] and restored normal walking speed and angular momentum under certain walking speeds and conditions [22, 253]. However, the inconsistencies in improvements in gait symmetry, metabolic cost, and joint and back loading across walking speeds, ambulation conditions, and research studies [254, 255, 253, 252, 241] demonstrate the need for improvements of active prostheses. This can be attributed to deficiencies in the control approach of such prostheses, for which determining the user's intended movement rather than the on-board hardware is currently the main challenge and bottle neck of the system.

There are a variety of control schemes designed to determine an active prosthesis' desired state (torque, stiffness, etc.), which can be either gait phase dependent, with a separate controller for each pre-determined phase, or gait phase independent with a single controller throughout the gait cycle. While gait phase dependent controllers can better constrain and simplify estimations, they lack the ability to apply changes within their defined phases, which can be important for tasks such as ballistic movements. Regardless of the chosen approach, there are a number of paradigms for determining desired states (for gait phases or whole cycles) including models based on damping [191], impedance [183], reflex behaviour [181], and tibial angles [256]. All of these methods rely on data from inertial measurement units, which are limited in their ability to capture the large variability in locomotion across people and do not provide a direct interface between the prosthesis and the user's intentions. An alternative approach is the use of the residual muscles' electrical activity (electromyography, EMG) for prosthetic control. Although most uses of EMG for lower limb prostheses have focused on locomotion activity recognition [257, 258, 200, 199], some researchers have also included EMG signals for torque modulation during plantarflexion [202, 259] or throughout the gait cycle [260]. This has been done mostly for theoretical exploration, which demonstrated benefits during stair ambulation in one study [202] and indicated a need for visual feedback of the muscle activity [260] in another. Other studies have reported an offline analysis of an EMG-based autoregressive model for prediction of sagittal plane ankle kinematics [261] as well as virtual control of multiple degrees-of-freedom

(DoFs) based on an EMG pattern recognition algorithm [205]. However, these methods have not been tested in real time during locomotion. Furthermore, all of these efforts have been focused on a single DoF ankle kinematics with no inclusion of stiffness control.

The human ankle operates in all three planes of motion while most of the current prostheses do so only in the sagittal plane. Late studies have demonstrated the importance of the frontal plane ankle motion for amputees during activities of daily living [262], sidestep cutting while walking [247], and for whole-body angular momentum [253]. The recent work by Clites *et al.* [194] has included a frontal plane control for active modulation of two DoFs of a transtibial prostheses and investigated stiffness control, employing EMG and IMU information within its framework. Its ability has been evaluated in real time in amputees, with promising results in the case of the amputee with an amputation procedure including an agonist-antagonist myoneural interface (AMI) [194]. However, the results for the amputees with a standard transtibial amputation (without AMI) were less consistent and the implemented joint stiffness control investigated was binary (stiffen or not).

Ankle joint stiffness is another important component in transtibial amputee prosthetic control. Its adjustment during locomotion has been suggested as the mechanism for changing speed and controlling downward and forward momentum during locomotion in humans [41, 37]. Recent studies have shown its variation during walking [33] and have emphasised the significance of transtibial amputee prosthesis stiffness for gait stability [263], stair ambulation [264, 265], with change of direction [266], and for balance [267]. Although great efforts have been made to measure active ankle joint stiffness [43, 33, 34, 44], less has been done for its active modulation within transtibial amputee prostheses. There are a few proposed stiffness control schemes for prosthesis design [268, 269], but only one recent study presents active single DoF ankle stiffness control [270] and this was done in simulation. In this chapter, I aim to address the gap in active adjustment of ankle joint stiffness while still providing adequate position control, targeting both the frontal and sagittal plane in real time. The proposed approach is a two DoFs active position and stiffness (2DAPS) control algorithm based solely on surface EMG. It has been tested in able-bodied and amputee people for voluntary control while standing and during walking on a treadmill (natural foot movement - no required prescribed movement) with promising results

for a human-integrated prosthesis control interface.

2.3 Methods

2.3.1 2DAPS Prediction Algorithm

A 2DAPS predictive algorithm was developed to compute simultaneous and proportional estimates of foot kinematics and virtual ankle joint stiffness in two degrees-of-freedom (DoFs) from muscle signals of the lower leg. Control information was extracted from a training set of muscle signals (see below) using a semi-supervised non-negative matrix factorization (NMF) algorithm [271], obtaining "DoF primitives" representing virtual forces around the ankle joint. The magnitude of the foot motion was obtained by a DoF-wise difference of the primitives with the direction determined by the sign of the value, while the stiffness was determined by the magnitude of the "antagonist primitive" of the main DoF (see Figure 2.1). The main DoF was considered as the one with the larger absolute value of its primitive as estimated by the NMF algorithm. In this way, a single stiffness output is provided, which is the antagonist

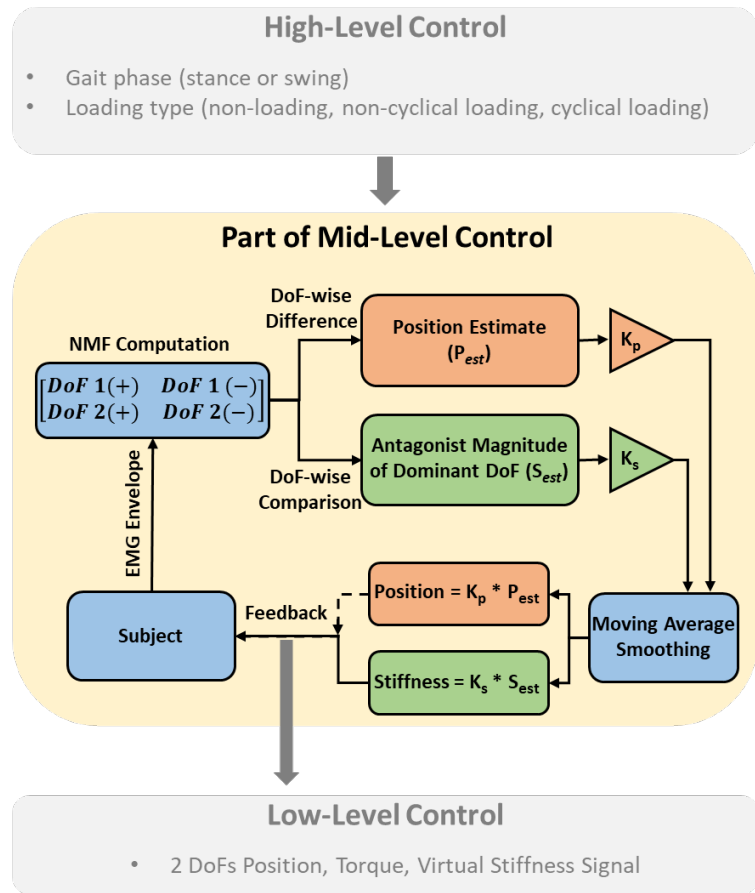


Figure 2.1: Flowchart of the 2DAPS control algorithm (yellow) as part of the overall controller. DoF 1 represents plantarflexion(-)/dorsiflexion(+), DoF 2 represents inversion(-)/eversion(+), and K_p and K_s represent the gain coefficients for position and stiffness respectively. Feedback for position is given only in Experiment 1, which is indicated by the dashed line.

primitives of the main DoF, even when the movement is a combination of both DoFs. However, this signal can be dissociated for the sagittal and frontal plane primitives by using the antagonist primitives from both DoFs to separate stiffness in the two DoFs. This approach for stiffness estimate was physiologically inspired as the active component of stiffness (due to muscular activity) is controlled mainly by muscle co-contraction [45]. Thus, the virtual representation of the "main" antagonist activity is assumed to represent the changes in stiffness as determined by agonist-antagonist co-activation. It is relevant to note that we did not aim at an exact estimate of the biological stiffness but rather we attempted to provide a control signal associated with stiffness that the user could control in a natural way by co-contraction. This was opted for because of the intended use of the signal as an overall stiffness step change as well as because of the difficulty in measuring active biological joint stiffness during the gait cycle, including the requirement of perturbation [33]. Both the kinematics and stiffness estimates were scaled between 0 and 1 using gain coefficients and smoothed using a moving average filter (length of 4 with an overlap of 3 estimates), to obtain the final virtual stiffness and kinematics feedback for the participants. In real time, each prediction was based on a 125-ms interval of EMG envelopes, extracted by band-pass filtering (20-500 Hz), rectification, and low-pass filtering (5 Hz) the EMG signals. Estimates were thus obtained at a frequency of 8 Hz, which is within the optimal delay for a prosthetic controller [272, 273]. In the context of this chapter, the 2DAPS algorithm is used purely as a feedback mechanism for feedback and performance comparison (in case of the kinematics). Thus, Experiment 1 aims to answer if this algorithm can provide reliable feedback for voluntary control of position and virtual stiffness signal (a signal separate from position that relates to biological active joint stiffness that arises from muscle co-contraction) in 2 DoFs. Consequently, Experiment 2 aims to evaluate what happens to the kinematics predictions during gait walking, when the foot movement is unconscious, and if users are still able to consistently modulate the provided virtual stiffness signal even during gait. In the context of a hierarchical control scheme, like the one presented in Figure 1.5 in Chapter 1, the 2DAPS prediction algorithm presented here (see yellow block in Figure 2.1) serves as part of the mid-level control, and the gray blocks in Figure 2.1 illustrate the high- and low-level control that will be introduced later in the thesis.

2.3.2 Subjects

Brief EMG data collection (comprising the aforementioned training set) is required for the 2DAPS algorithm. The data collection procedure consisted of instructing the user to stand in front of a screen and follow the movement of a circular target (cue) on a screen by performing motions of their (phantom) foot. The vertical movement of the cue represented ankle dorsiflexion(up)/plantarflexion(down) while the horizontal reflected eversion(right, for a right leg)/inversion(left, for a right leg). Each direction was repeated four times, after which the data collection was completed. The participants were standing with straight knees during the muscle activation so that the recorded limb was loaded under their body weight. Following this, the direction and stiffness estimates were scaled between 0 and 1, using the previously mentioned gains. This whole procedure typically lasted 5 to 10 min, after which the participants were provided with a simultaneous continuous and proportional control of the cursor in 2 DoFs and were asked to complete the tasks by (imagining) performing (phantom) foot movements (and stiffness). While the instructions for foot movements are simple and clear, the instructions for stiffness were given in a more naturalistic way, presenting a scenario, due to the unusual task for controlling joint stiffness (an otherwise subconscious act). The exact scenario given to the participant is to imagine walking on ice or unstable ground and try to re-enact the adjustments that they are doing while they are given the feedback of the algorithm. In this way, there is no explicit instructions for what to do (i.e. co-contract the antagonist muscle), thus not revealing how the algorithm works. At the same time it gives the participants a feedback so they can learn the relationship between their adjustments and the foot movements and stiffness magnitude, provided by the algorithm.

Eight male able-bodied (age: 25.5 ± 2.5 yrs) and two male transtibial amputee (Subject A: age - 34 yrs, K-level - 3, residual limb length - 20cm, prosthetic leg - Össur Pro-Flex, Subject B: age - 25 yrs, K-level - 4, residual limb length - 18.5cm, prosthetic leg - Blatchford EchelonVT) individuals participated in Experiment 1, and eight able-bodied (4M and 4F, age: 26 ± 3 yrs) and one male transtibial amputee (Subject B) individuals participated in Experiment 2. One able-bodied and one amputee individual (Subject B) participated in both experiments. Sub-

ject A underwent amputation 1 year before the experiments following trauma. He presented denervation of anterior compartment muscles of the leg and targeted sensory reinnervation of the posterior tibial nerve sensory branch onto the gastrocnemius. Subject B had an amputation surgery 3 years prior to the experiment due to a chronic pain condition and a revision surgery 1 year post-amputation. All participants had no known neurological disorder and no prior knowledge of the experimental tasks, thus were considered as naïve in terms of both experiments. The experimental evaluations were approved by the research ethics committee at Imperial College London (18IC4605) and were conducted according to the declaration of Helsinki. Written informed consent for the study was provided and signed by all subjects prior to their participation.

2.3.3 Electrodes and Markers Configuration

For both experiments, the muscle activity of the dominant (for able-bodied) or residual (for amputees) lower leg was recorded using three semi-disposable adhesive 8x8 surface EMG electrode grids (192 electrodes in total) with 10 mm interelectrode distance (OT Bioelettronica, Torino, Italy). Grid #1 was placed alongside the lateral end of the tibia and grid #2 next to it; grid #3 was mounted 3 cm distal to the medial end of the tibia (see Figure 2.2). Each grid was located on the belly of the respective muscles - tibialis an-

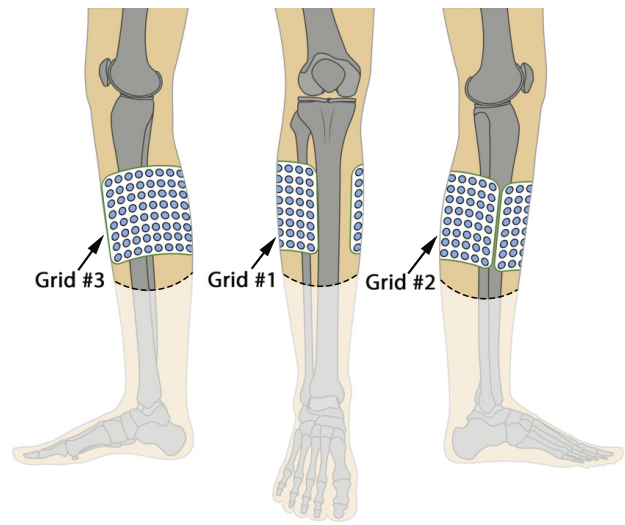


Figure 2.2: Illustration of electrode placement, kept consistent between amputee and able-bodied participants.

terior for grid #1, lateral gastrocnemius for grid #2, and medial gastrocnemius for grid #3. Reference electrodes were placed on the ankle (knee for amputees) and the wrist of the recorded side.

For Experiment 2, in addition to the EMG electrodes, reflective markers were placed on both legs in accordance to the Oxford Foot Model [274]. For the transtibial amputee participant in Experiment 2, the area and placement of electrodes were kept consistent with the above description, but the electrode density was smaller (down to 64 channels out of 192 - see Figure 2.3B) due to the limitations of the wireless

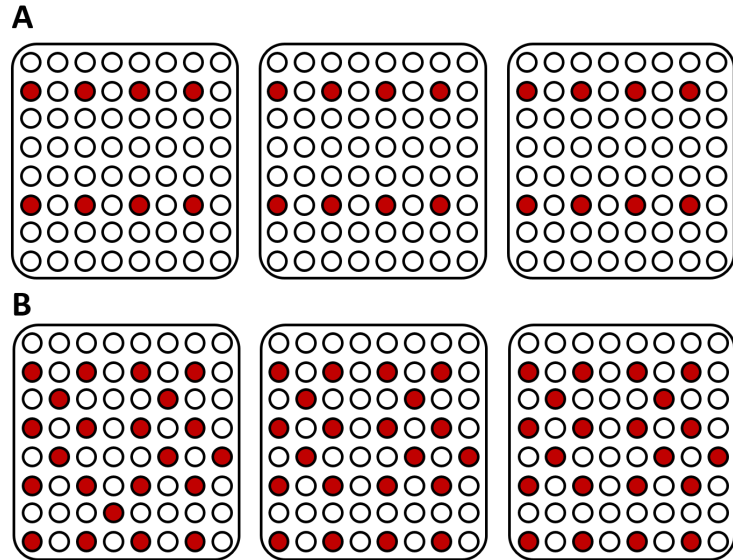


Figure 2.3: Reduced electrodes (A) and wireless EMG (B) configurations for the experiments.

EMG hardware used for the second experiment (see below). Furthermore, in both experiments, a subset of 24 EMG electrodes was investigated to analyse the robustness of the algorithm when varying the number of electrodes. For this purpose, the electrodes were reduced equidistantly in a circumferential manner, incurring no position bias (see Figure 2.3A).

2.3.4 EMG and Kinematics Recording Setup

Monopolar EMG signals were acquired using an amplifier (EMG-USB2+, OT Bioelettronica, Turin, Italy) with the highest gain allowing no saturation (typically 200-500 for able-bodied and 2000 for amputee participants) at 2048 Hz sampling rate and 12-bit A/D conversion. A wireless EMG amplifier (Sessantaquattro, OT Bioelettronica, Turin, Italy) was used for the amputee subject in Experiment 2, allowing in-socket recording, with sampling at 2000 Hz and 16-bit A/D (no gain factor needed). Leg kinematics were recorded at 100 Hz via a 10-camera motion capture system (Vicon, Oxford, UK). Synchronization between the EMG and motion capture systems was achieved using a common signal (voltage step) recorded by both systems.

2.3.5 Experimental Protocol

Experiment 1: Virtual Cursor Control Experiment 1 investigated the algorithm’s capability as a myoelectric interface for voluntary movement and stiffness control applicable for stationary tasks such as getting on tip-toes for reaching while standing, maintaining balance by changing stiffness and/or direction, foot readjustment, etc. It was tested by asking participants to complete target matching tasks on a screen with a user-controlled circular cursor (control provided by the algorithm described in Section 2.1). The position of the cursor in the two control directions represented the DoFs and the size of the cursor the stiffness.

Task 1 consisted in matching the position of 20 consecutively introduced targets (Figure 2.4A), while task 2 required matching both the position and diameter of 20 consecutively introduced targets. Task 2 was repeated with the reduced number of channels illustrated in Figure 2.3A.

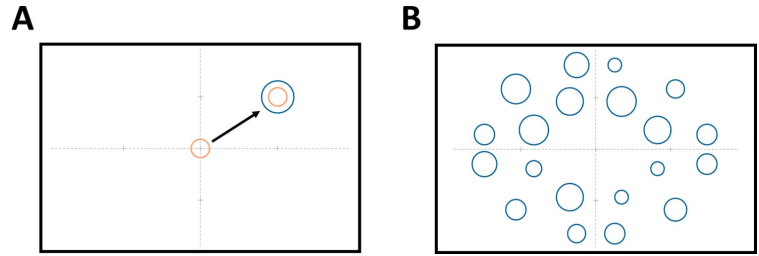


Figure 2.4: Illustrations of the position matching task (4A) and of possible positions and diameters for the targets (4B) in Experiment 1.

In order to successfully match a target, the participant had to hold the required position or position and diameter for at least 300 ms. The time interval between targets was 5-10 s, depending on time of completion, and a rest period of 3-5 min was provided between tasks to avoid muscle fatigue. Target’s positions and diameters were randomized from a set of values (illustrated in Figure 2.4B). The diameter set discretization (8 levels - 12% change) was selected to be within the range of perceivable changes in stiffness by amputees [275]. The requirement for a successful diameter match was a 75% area overlap between the cursor and the target in addition to the position requirement for the cursor to be inside the target.

Experiment 2: Walking Virtual Stiffness Control Experiment 2 investigated the ability of the algorithm to provide a reliable stiffness control during walking and to evaluate the quality of the kinematics estimates during the task and under the natural foot movement condition. The

stiffness control and kinematic estimates provided here were not implemented into the prosthesis control of the participant in real-time. This was due to the lack of prosthetic hardware that would allow us to do that. Instead, they were computed and recorded in real-time and later used for comparison between the recorded kinematics and the predicted ones (in the case of foot position) and for investigation of the ability of participants to output three distinctly different levels of virtual stiffness signal. The prosthetic hardware used during the recordings including a person with an amputation was their personal one, which was completely passive and included a carbon foot. The experiment was conducted on a treadmill (quasar® med, h/p/cosmos, Munich, Germany) in a motion capture lab to record the movement of the reflective markers attached to the participant (see Section 2.3.4). A treadmill was chosen as, although there are known differences between over ground and treadmill walking, the study serves as a comparison between algorithm estimates and motion capture recorded kinematics rather than an exploration of the biomechanical effects of the algorithm implementation. The task consisted in matching a virtual stiffness level, with the provided feedback from the algorithm on a screen in front of the subject, while walking on a treadmill. Participants walked at three walking speeds (slow, normal, fast), each of which was repeated three times, as well as at their normal walking speed with the reduced number of EMG channels condition (repeated three times as well). The normal walking speed was determined by asking the subject to walk at their natural pace and the slow and fast walking speeds were set at a ± 1 km/h with respect to normal. Each of the 12 walking trials lasted 1 min, consisting of 10s of walking with no stiffness control required (NSR), followed by three 10s stiffness requirements (low, med, and high set at 20%, 40%, and 60% virtual stiffness) with 5s NSR in between, and ending with another 10s of NSR walking (see Figure 2.5A). These targets were selected to represent three significantly different levels of the normalized virtual stiffness signal. The low level was selected at 20% to set it high enough to be distinct from the NSR level, and then increments of 20% were added, which determined the other two levels. The 20% increments were selected not only because they would be high enough to be distinct, but also because the highest one would not be too strenuous for the individuals in an effort to avoid muscle fatigue. Electrode placement and algorithm training procedures were the same for both experiments and walking speeds and

stiffness cues order was randomized for each trial. The reduced EMG electrode condition was randomly assigned to the first three or the last three trials. With this design, Experiment 2 aimed to provide evidence that individuals could vary the stiffness control signal with the provided interface while the interface predicted their ankle kinematics. Such stiffness control signal can be applied for an overall step change in a prosthesis ankle joint stiffness during walking over uneven terrains, for different ambulation modes, or for sudden halt or change in direction. Thus, even though a pre-defined stiffness profile/relationship (i.e. with load) over a gait cycle remains the same, the overall stiffness level can be modulated if/when needed. This aims to bridge the discrepancy of overall ankle joint stiffness that exists between the intact leg and the prosthesis (for unilateral amputations) and during different ambulation modes (for both unilateral and bilateral amputations) with the prospect of aid in gait symmetry recovery.

2.3.6 Kinematics Data Processing

In Experiment 2, to obtain foot kinematics from the motion capture recordings, a subject-specific skeleton calibration [276] was performed using data from a static trial and measurements of height, weight, knee and ankle width taken for each participant. After the scaling, inverse kinematics computation was performed in Vicon Nexus 2.8 using the provided Oxford Foot module. Following this analysis, foot strike and foot-off events were labelled, and the extracted kinematics were downsampled from 100Hz to 8Hz for comparative reasons, as the algorithm's

prediction frequency was 8Hz. The predicted kinematics were also post-processed for comparative reasons by removing the offset between the axes of the motion capture kinematics and the predicted ones, determined on a subject basis. The predicted kinematics were further high-pass filtered (0.7 Hz for the highest

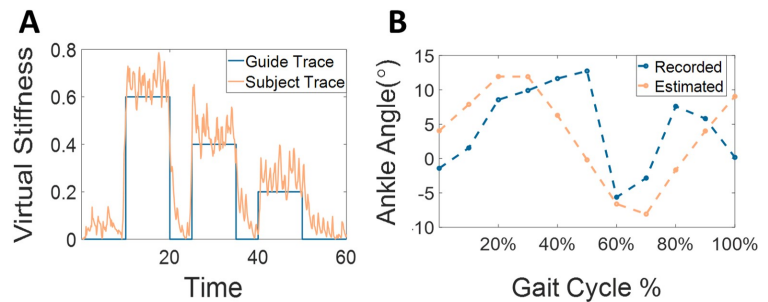


Figure 2.5: Able-bodied participant example of Experiment 2 stiffness matching task (5A) and an estimated (one-sample delayed) and motion capture recorded gait cycle (5B) used for gait metrics calculations. The first rocker in 5B is not visible due to down-sampling of the recording.

stiffness section and 0.4 Hz for the rest) to remove low frequency artifacts.

Estimates were also found to be one sample (125ms) ahead of the recorded kinematics for all participants, likely due to the electromechanical delay [277], thus all kinematics comparisons were done with a one-sample delayed estimation. Gait cycles for each trial were extracted from the labeled foot strike event and root mean square error (RMSE) and the cross-correlation (XCOR) between the down-sampled motion capture and the EMG-estimated gait cycles (see Figure 2.5B) were computed, providing two comparison metrics per gait cycle. For the amputee participant, gait cycle ankle kinematics, used for comparison to the algorithm’s estimations, were taken from the contralateral leg.

2.3.7 Statistical Analysis

The algorithm’s performance in Experiment 1, was measured based on number of targets reached, near misses, and average time to target. A near miss was defined as a successfully reached target but with failure to hold the target’s position and diameter (if required) for the dwell time (300ms). Metrics comparisons were performed using a two-way repeated measures Anova with task and direction as the investigated factors and null hypothesis being task and/or direction having no effect on the performance metrics. If the null hypothesis was rejected, a post-hoc analysis (using a Bonferroni correction) was performed. The task factor levels were position (Pos), position and stiffness (PS), and position and stiffness with reduced number of channels (PSR) and the direction factor levels were up, down, left, right, and 45° diagonals (four targets per direction level). Required assumptions for normality, independence, and sphericity were checked before any statistical analysis. IBM SPSS Statistics (IBM Corp. Released 2013., Version 25.0) was used for the experiment’s statistical analyses.

Experiment 2 analysis was performed in R [278] using linear modelling with null hypothesis being that experimental conditions having no effect on the stiffness control and comparison metrics. For able-bodied subjects, linear mixed effects analysis was performed using the *lme4* package [279] in R to assess the effect of different experimental conditions on the stiffness control and the gait cycle comparison metrics. For the trials utilizing all EMG electrodes, the required

stiffness level, walking speed, and their interaction were set as the fixed effects for the model, with subject ID set as a random effect. For the comparison between full and reduced number of EMG electrodes at normal walking speed, the fixed effects were the required stiffness level, number of electrodes, and the interaction between them, and the random effect was the subject ID. The results of the amputee subject were analyzed with a linear model (*lm*) investigating the same fixed effects but without a random effect. The distribution for the cross-correlation (XCOR) and stiffness comparisons was changed to a beta distribution for both able-bodied and amputee analyses as it is a percentage/proportion data. This was performed using *glmmTMB* [280] (for mixed-effects models) or *betareg* [281] (for fixed-effects models) packages in R. After the models were constructed, likelihood ratio tests of the full model against reduced effects models were performed to assess the impact of the different effects. In addition, post hoc estimated marginal means (EMMs) analysis using *emmeans* [282] with a Bonferroni correction in R was performed to compare the EMMs of each metric at each stiffness level based on the walking speed. EMMs, confidence intervals and significance were obtained using these tests. Assumptions for linearity, normality of residuals (when normal distribution is used), homoscedasticity, and absence of influential data points and co-linearities were checked before any statistical analysis.

2.4 Results

2.4.1 Experiment 1

The proposed control approach for a myoelectric interface provided a reliable and intuitive output allowing for gait phase independent simultaneous and proportional control of 2 DoFs and virtual joint stiffness using solely EMG signals from the lower leg muscles. Utilizing the full set of EMG electrodes, the able-bodied participants achieved 72.5% and 68.1% success rate on average for Pos and PS matching tasks respectively (Figure 2.6). Both of the amputees achieved higher success rates than the able-bodied individuals (82.5% and 72.5% for Pos and PS tasks respectively) with comparable average time to target (7.8s and 9.9s for Pos and PS

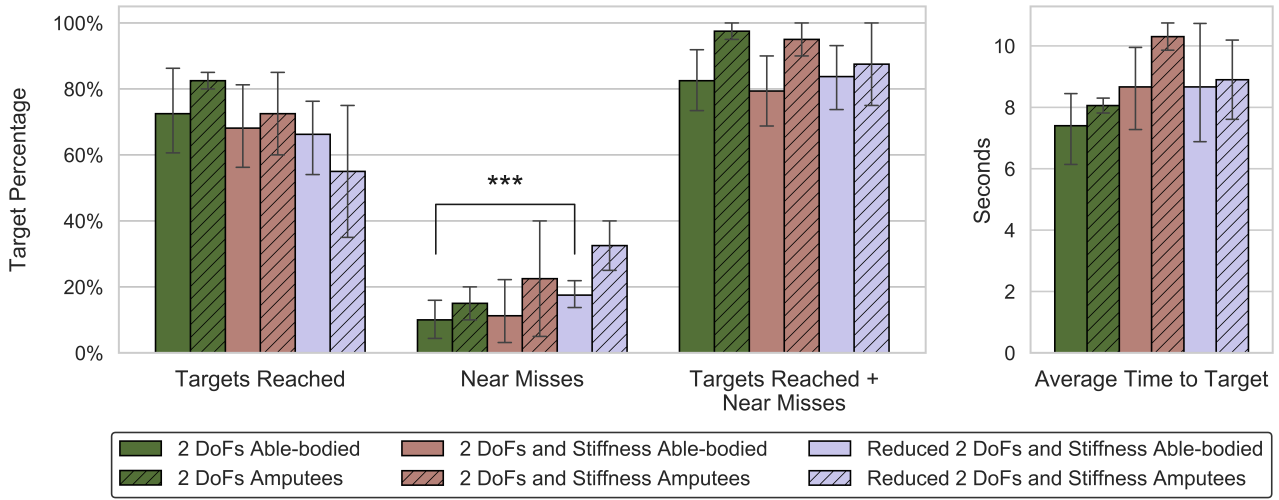


Figure 2.6: Experiment 1 metrics comparison (97.5% CIs).

tasks respectively compared to 7.4s and 8.6s in able-bodied participants). For the reduced EMG electrodes condition, able-bodied participants achieved average success rate of 66.2%, with 8.66s average time to target. However, when decreasing the number of channels, there was a steep decrease in target success rate and an increase in near misses for the PSR task in one of the amputee subjects (Subject B) due to his denervated anterior compartment muscles (see section 2.3.2). The participant could still reach most of the targets, as can be observed by the combined targets reached and near misses (Figure 2.6), but often could not hold the position and diameter for the required time. This was not observed in the other amputee participant during the PSR task, where there was a slight increase of success rate, likely due to task learning. On average, the amputees' target success rate was 55.0% with 8.9s time to target. The statistical analysis in able-bodied participants revealed no significant differences between the target success rate and average time for Pos, PS, and PSR trials. The near misses comparison revealed significant differences between the tasks ($p = 0.001$), and the post-hoc pairwise comparison revealed significance ($p = 0.0003$) between the number of near misses during P and PSR tasks (increased from 10% for P to 24% for PS task). The analysis for directional dependence of the result revealed no significant difference in performance metrics between all tasks ($p > 0.15$).

2.4.2 Experiment 2

The results of Experiment 2 provided clear indication of the algorithm's ability to allow voluntary virtual stiffness control during walking (Figure 2.7). All participants (able-bodied and amputee) were able to output 4 significantly different ($p < 0.0001$) levels of stiffness (3 voluntarily controlled + neutral level) across all walking speeds, including the reduced EMG electrodes condition. The kinematics prediction during the trials also demonstrate high gait cycle XCOR (Figure 2.8A) especially in the frontal plane ($>75\%$ for the sagittal and $>90\%$ for the frontal plane).

All gait cycles predictions were within the physiological range with a gait cycle RMSE of $<7.5^\circ$ in sagittal and $<3^\circ$ in frontal plane (Figure 2.8B), typically representing an overshoot estimation, which is indicated by the high XCOR. The results of the gait cycle metrics comparison for the amputee participants revealed a similar level of RMSE and cross-correlation across the experimental conditions in both planes of motion (Figure 2.8A and B).

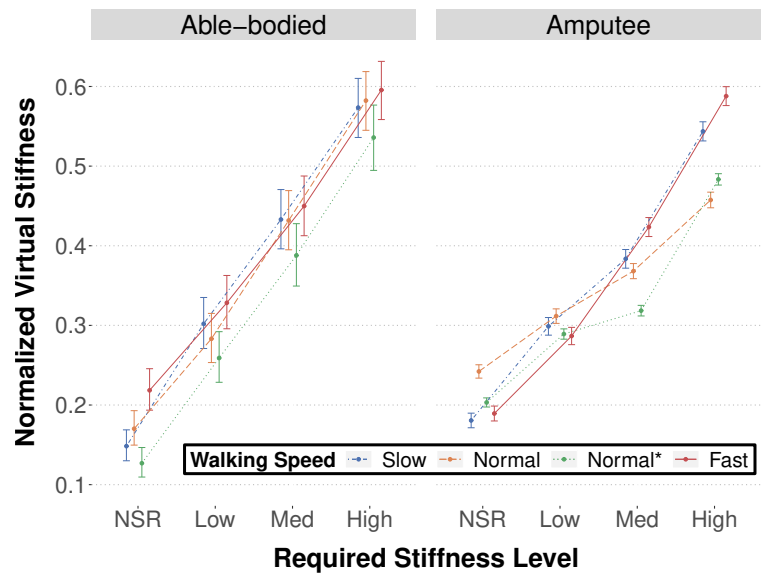


Figure 2.7: Results for the stiffness control task in Exp 2. The "*" in the legend indicates the reduced electrodes condition.

There were statistically significant differences across walking speeds, required stiffness levels and electrode number condition for the gait cycle RMSE (Figure 2.8B). Most notably for able-bodied participants, there was a higher sagittal RMSE for the NSR stiffness requirement at normal and slow walking speeds and a higher sagittal RMSE during the trials with reduced EMG channels in comparison to the full set at normal walking speed. However, the overall mean RMSE difference was within 1.5° for the sagittal plane and 0.5° for the frontal plane. Similarly, there were some statistically significant differences for the amputee participant's gait cycle RMSE (Figure 2.8B) - higher RMSE at fast walking speed for the low stiffness requirement

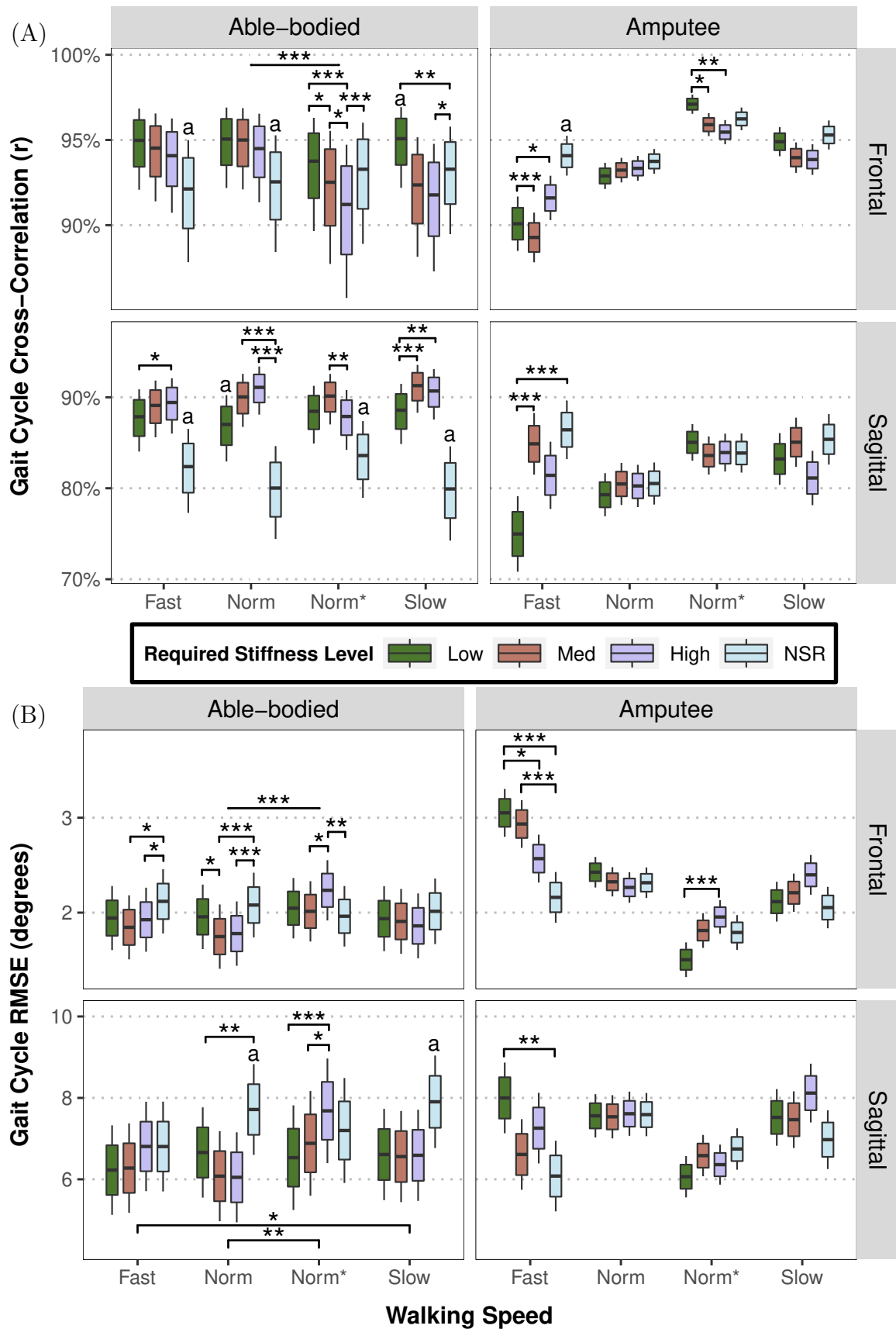


Figure 2.8: Cross-correlation and RMSE comparison results computed at a complete gait cycle level across required stiffness levels, walking speeds, and plane of motion for both able-bodied and amputee participants (97.5% CIs). NSR stands for No Stiffness Required. The “*” in x-axis label indicates the reduced electrodes condition. The “a” indicates significance of $p < 0.001$ against the rest of the stiffness levels within a walking speed unless additionally indicated otherwise. No-tip lines are for between-speed significance in frontal planes.

compared to NSR in sagittal plane and the high and NSR requirements in frontal plane as well as higher frontal plane RMSE during the high stiffness requirement compared to the low one for the trials with reduced EMG electrodes. However, all these differences were within 2° for the sagittal plane and $0.5^\circ - 1^\circ$ for the frontal plane. It is worth mentioning that the fast walking speed results for the amputee were computed from a single trial (instead of three trials) due to poor motion capture data prohibiting the trials' reconstruction. There were significant differences for the gait cycle XCOR in able-bodied participants across conditions, most notably a lower XCOR during the NSR stiffness requirement across all walking speeds in the sagittal plane.

This could be explained by the lower overall muscle activity in able-bodied participants for this condition as the algorithm relies solely on muscle activity. This was not noted for the amputee as there was not such a significant decrease of muscle activity between the different stiffness conditions. For the amputee, there were a few significant differences in XCOR, most notably at fast walking speed, exhibiting a lower XCOR for the low stiffness requirement (compared to medium and NSR) in the sagittal plane and higher XCOR for the NSR stiffness requirement (compared to the rest) in the frontal plane.

A further analysis of the metrics at each sampling point (125ms) revealed differences only around the heel strike event for able-bodied participants and around the terminal stance for the amputee participant. This was due to the low muscle activity during these phases and the different muscle activation between the able-bodied and the amputee participant. For able-bodied participants, the lowest average muscle activity, calculated over 125ms window, was around the heel strike ($24\% \pm 9.4\%$), which was 18.6% lower than the amputee's average ($42.6\% \pm 5\%$) for that phase; while for the amputee, the lowest average muscle activity was around terminal stance ($26.4\% \pm 9.7\%$), which was 29.5% lower than the average for the able-bodied participants ($55.9\% \pm 13.6\%$) for the same phase.

2.5 Discussion

The developed 2DAPS algorithm has demonstrated its ability to provide real-time voluntary control of virtual position and stiffness while standing (average success rate of 72.5%, 68.1% and 66.2% respectively for Pos, PS and PSR tasks in able-bodied and 82.5%, 72.5% and 55.0% respectively in amputees), as well as voluntary virtual stiffness control and satisfactory estimates of foot kinematics during walking in both the frontal and sagittal planes of motion. These results indicate a promising prosthetic interface that can offer user integration, allowing voluntary adjustments in stiffness of the ankle joint throughout locomotion. Such active real-time 2 DoFs stiffness control has never been achieved before and can have a significant impact across locomotion activities as well as for standing balance. The 2DAPS algorithm was used with sole input from surface EMG (no feedback loop) and without being based on gait phases and parameters or require prior training of the participants. This opens up the possibility to utilize an already available IMU input from the prosthesis and close the loop, which can facilitate the performance in the areas where the EMG input may not be sufficient. In this way, a better performance can be achieved while keeping the benefits of user integration including active stiffness control that the 2DAPS algorithm offers. One general limitation of the study, however, is the small number of amputee participants and lack of interfacing the algorithm with an active 2DoFs prosthesis, which is addressed in Chapter 3.

The results from Experiment 1 confirmed observations from previous studies about the possibility of voluntary ankle joint position control [194, 283] and adds an additional two DoFs stiffness control without deterioration of the algorithm's performance (Figure 2.6). Due to the nature of the classification (continuous and proportional rather than discrete classes) and the success criteria, the success rates can be perceived as lower in comparison to previous studies. However, if only target reaching is considered, without the hold criteria, the average rates for the two amputee participants are 97.5% and 95% for Pos and PS tasks respectively (Figure 2.6 - Targets Reached + Near Misses). This is close to the 100% targets reached for a similar task in below knee amputees reported by Clites *et al.* [194], with an addition of higher target position resolution and a continuous stiffness control variable, albeit with a significantly higher number

of EMG electrodes. There was a variability in able-bodied participants' performance (lowest success rate, noted in the same participant, of 60%, 55 %, and 45% for Pos, PS, and PSR task respectively) due to the lack of previous training and general differences in performance across individuals for newly introduced tasks. Such differences have been seen before in myoelectric control studies and are expected to decrease with training [284, 285, 286]. The only decline of performance, reflected in decreased success rate (from 85% down to 35% for PS and PSR task respectively) and increased near misses (from 15% to 40% for PS and PSR task respectively), was exhibited during the PSR task with one of the amputees. This was most likely due to the fact that his anterior compartment muscles were denervated during amputation. As the algorithm relies on EMG information and the electrode reduction was not biased, more than 1/3 of the information was lost when reducing the number of electrodes, which in turn influenced the controller's stability. However, the results of this participant with the full set of electrodes demonstrate the ability of the 2DAPS algorithm to provide two DoFs position and stiffness control even when the muscle innervation has been severely damaged. This was possible as the algorithm does not rely on prior knowledge of muscles' physiological actions but rather on the individual's muscle activation patterns during attempted movements of the phantom limb. Thus, it can expand the applicability of the algorithm across amputee populations with different neurological disorders, whom will be evaluated in further studies, with the cost of a larger number of electrodes. Alternatively, a smaller number of electrodes with a personalized electrode placement can be used, where the electrodes are placed over the areas of muscle activation rather than equidistantly around the stump, which is a clinically-achievable solution. The demonstrated stiffness control resolution (8 levels/12.5% difference), although representing a virtual signal rather than measured ankle joint stiffness, is in agreement with the findings of Shepherd *et al.* [275], which demonstrate a transtibial amputees' ability to distinguish stiffness differences of 8% in 75% of the trials. One limitation of Experiment 1 is the non-randomised order of tasks (increasing order of difficulty - Pos->PS->PSR), chosen due to lack of any prior training of the participants. Thus, further research would be needed to explore the effect of learning, reflected in the increased number of near misses (especially for the PSR task).

The outcome from Experiment 2 shows the extended capability of the 2DAPS algorithm to

reliably provide four different levels of voluntary stiffness control in conjunction with estimates for ankle joint kinematics in both sagittal and frontal planes during walking at different speeds. This is the first demonstration of simultaneous and proportional estimates of ankle position and stiffness control in 2 DoFs. Previously, Farmer *et al.* [261] developed an algorithm for single DoF ankle position control based on EMG signals, whose performance was evaluated by calculating an RMSE between the estimates and the amputee's contralateral limb kinematics (from motion capture) during treadmill walking at a constant self-selected speed. Their average RMSE results for one of the three amputee participants, using an EMG window of similar length to ours (130 ms), are comparable to the sagittal plane RMSE results presented here (6.3° compared to 6.49° presented here), with the other two amputee participants showing smaller errors ($\approx 3^\circ$ and 1.5°) [261]. However, the 2DAPS algorithm presented here offers not only an additional DoF but also novel 2 DoFs stiffness control capabilities. Farmer *et al.* further found a one-sample (100 ms) delay between the recorded kinematics and the estimates (similar to our study) as well as similar error distribution throughout the gait cycle - small error around heel strike and largest errors around terminal stance [261]. Furthermore, our findings on the increased muscle activity around heel strike and decreased activity around terminal stance corroborate a recent study on myoelectric activation patterns in transtibial amputees during locomotion [287]. Although this muscle activation may vary drastically across amputee participants, as indicated by Huang and Ferris [288], the analysis points towards the largest errors being around the lowest myoelectric activity, regardless of the gait phase in which this occurs (terminal stance for amputee or heel strike for able-bodied subjects in the current case). Another important note is the algorithm high XCOR in the frontal plane, which reflects its ability to accurately predict the ankle joint movement direction in that DoF. As such quantitative analysis has not been done before for the frontal plane, comparisons are not possible, but the high fidelity of this information can be very helpful for a prosthetic control. Thus, this can enhance prosthetic performance during activities of daily living [262], sidestep cutting [289], and improve whole-body angular momentum [253]. However, even though the results are promising, such implementation in a prosthesis for daily use would still need refinements since errors, especially around low muscle activation intervals, can be large (overall maximum error found was 19.6° and 6.2° for able-bodied and 14.4° and 5.2°

for the amputee participant in the sagittal and frontal plane respectively). Such irregularities would not be acceptable and are planned to be addressed by improving the algorithm and adding IMU sensor information that would be helpful during low muscle activation periods. Two notable limitations of Experiment 2 are the number of investigated activities (only level-ground walking) as well as the lack of an actively controlled prosthetic device. The algorithm integration in a prosthetic device is very important for a variety of reasons. The quality of estimation in the amputee participant was assessed by comparing it to the intact leg kinematics as previously done by Farmer *et al.* [261]. However, as amputees suffer from gait asymmetry, there may have been differences between the kinematics of the two feet compared to able-bodied individuals. Furthermore, the device implementation of the active stiffness control, which aimed to further alleviate gait asymmetry by providing an overall joint stiffness change, will also have an effect on the kinematics. Thus, investigating the interaction between the user and the device and how the implemented controller affects the overall biomechanics is important for the assessment of the overall utility of the algorithm in a real-life implementation. These study limitations will be addressed in the future as the novel active stiffness control offered by the 2DAPS algorithm presents a unique opportunity to explore such control in a variety of activities and potentially address the issues of uneven loading, which relates to increased osteoporosis rates and joint and back pain in lower limb amputees.

2.6 Conclusion

This work has presented a new 2DAPS algorithm that can provide real-time voluntary control of virtual foot kinematics and stiffness during walking, enabling a prosthetic interface for two degrees-of-freedom ankle joint control driven by electromyograph. This active real-time 2 DoFs stiffness control has never been achieved before. The amputee participants in this study were able to achieve comparable or better results than able-bodied individuals without any training, indicating the potential of the 2DAPS algorithm for its use in transtibial prosthetic control. The novel ability of the algorithm to provide a 2 DoFs stiffness control signal in addition to including the user in the control loop, has many implications for improvements in prosthetic performance

across activities of daily living and different locomotion modes and terrains. This addresses part of the needs and functional requirements for transtibial prostheses presented in Section 1.6, and will be used later, in Chapter 5, to provide user modulation to the prosthetic controller, inspired by how vertebrates actively modulate stereotypical gait patterns via supraspinal commands (see Section 1.4).

2.7 Supplementary Material - Marker Set

The marker set comprised a total of 21 markers per leg placed on anatomical landmarks of the lower limb, including anterior/posterior superior iliac spine markers, a thigh marker, and lateral femoral condyle marker (see Table 2.1 and Figure 2.9 below). The underlying biomechanical model consisted of five segments – one for the femur, one for the tibia, and three for the foot (hindfoot, forefoot, and hallux). Both the marker sets and the biomechanical model are part of the provided Oxford Foot Model [274] module in the Vicon Nexus software.

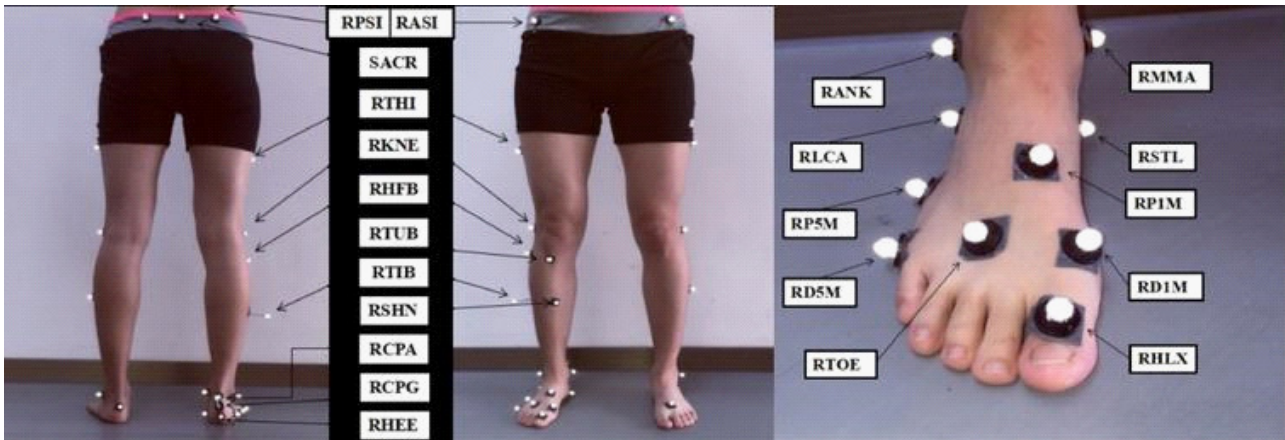


Figure 2.9: Marker set illustration (adapted from Wang *et al.* [290]).

Marker Name	Marker Anatomical Landmark
LASI/RASI	Anterior Superior Illiac Spine
LPSIS/RPSIS	Posterior Superior Illiac Spine
LTHI/RTHI	Lateral Mid-Thigh
LKNE/RKNE	Lateral Femoral Condyle
LTIB/RTIB	Lateral Mid-Tibia
LHFB/RHFB	Lateral Head of Fibula
LTUB/RTUB	Tibial Tuberosity
LSHN/RSHN	Anterior Aspect of the Shin
LANK/RANK	Lateral Malleolus
LMMA/RMMA	Medial Malleolus
LCPG/RCPG	Posterior End of Calcaneus
LHEE/RHEE	Heel
LPCA/RPCA	Posterior Calcaneus Proximal
LLCA/RLCA	Lateral Calcaneus
LSTL/RSTL	Sustaniculum Tali
LP1M/RP1M	1st Metatarsal, Proximal Dorsal
LD1M/RD1M	1st Metatarsal, Distal Medial
LP5M/RP5M	5th Metatarsal, Proximal Lateral
LD5M/RD5M	5th Metatarsal, Distal Lateral
LHLX/RHLX	Hallux

Table 2.1: Markers' names and anatomical positions

Chapter 3

Wearable System for Multisensor Prosthetic Control

As the development of this thesis' multisensor prosthetic controller requires data that has not been previously available, a supporting hardware had to be built to enable that data collection and the following testing of the algorithm. The previous experiments (reported in Chapter 2), especially the ones involving recording and outputting data during gait, highlighted certain engineering advancements, which needed to be done from both system and user standpoint. Furthermore, additional sensing technology, namely a six-axis IMU, also needed to be added, as this signal was planned to be used as a supplementary input for the overall prosthetic controller presented in Chapter 5. The choice for adding IMU was made based on the fact that almost all commercially available prostheses contain one, in addition to the need for mechanical sensors to provide reliable information about the prosthetic state as well as provide additional information for velocity and acceleration of the foot for the controller presented in Chapter 5. The role of the IMU will be clarified further in Chapter 5, while this chapter focuses on all the hardware and software implementations for further data collection and prosthetic control.

What is the optimal electrode density and position for the lower leg, how should the software be structured, what is the ideal cable routing and wearable equipment placement - these were all questions that I've had experience with beforehand and enabled me to build a reliable system.

This is vital because so much of the research done in this area pertains to ideal lab conditions and my aim here was to create a setup that is really easy to use and portable. In this way, the developed algorithm and future approaches can be tested in real conditions, outside the lab, requiring no tethered wires or computers other than a smartphone. That would allow for true testing and validation of such systems in a real-world scenario. This chapter describes all the hardware and design developments that have enabled this. Section 3.1 and 3.2 of this chapter will cover all the user and system requirements, enlisting them and demonstrating the manner they were addressed. Following this, Section 3.3 will further describe the software implementation details and the controller computational testing pertaining to execution time and data communication, evaluating them against the previously listed requirements.

3.1 Garment and Electrode Grid Design

One of the first things experienced during my previous experiments was to do with cabling and equipment housed around the body. This gave rise to the need to develop a wearable setup, which had to accommodate for people with and without amputations. Below are the requirement specifications that needed to be addressed for this part of the setup.

3.1.1 User Requirements Specification (URS)

1. Garment comfort and size adaptation - one-size-fits-all design that is as low-profile as possible.
2. Completely wireless technology - all cables are to be housed on the user's body. This arose during Experiment 2 in Chapter 2, where cables prevented any experiments outside treadmill gait, presented a trip hazard, and were a potential cause of gait changes.
3. Balanced equipment weight distribution, which is closer to the hip, due to the fact that unbalanced weight further below the knee would affect gait.

4. Unobtrusive HDEMG electrodes - my previous experience in Chapter 2 indicated that the user needed electrodes that were thinner than previous ones, with cable routing that was not causing pain due to pressure difference and impingement at the socket level.
5. Consistent electrode placement - allow for ease of placement and consistency of data collection between participants and experimentalists.

URS 1 required an iterative approach for the development of the garment. Fitness thermals were used as the base for the garment due to their ability to stretch and retain form across a variety of sizes. The iterative versions can be seen in Figure 3.1, which include the evolution of the garment from long trousers with in-sewn pockets and cable routing, to the shorts version (V3) with Velcro TM strips as attachment places for equipment and cable routing. This final form allows for a large range of placement options that is needed due to the differences in length and circumference of users' thighs, while also reducing the size of the padded packs that contained the equipment and were provided for cable routing. This final configuration with the battery pocket at the waist, the microcontroller pack and velcro attachment on the back of the thigh, and the amplifier pack and Velcro TM attachment at the front of the thigh along with the cable routing and the sensors can be seen in Figure 3.1.

URS 2 was addressed in three different ways - changing the amplifier, using a microcontroller, and including equipment pockets on the garment. These changes came with further requirements. Changing the amplifier required changing the acquisition software (further discussed in the next section). The switch to a microcontroller required an introduction of a battery power source. Consequently, both of these changes also required introduction of pockets to house this equipment. This was successfully done and the overall garment development can be seen in Figure 3.1.

URS 3 prompted the placement of the equipment pockets for the microcontroller on the hamstring and for the amplifier on the quadriceps, due to their similar weight, with the battery pack placed on top of the gluteus (as seen in Figure 3.1).

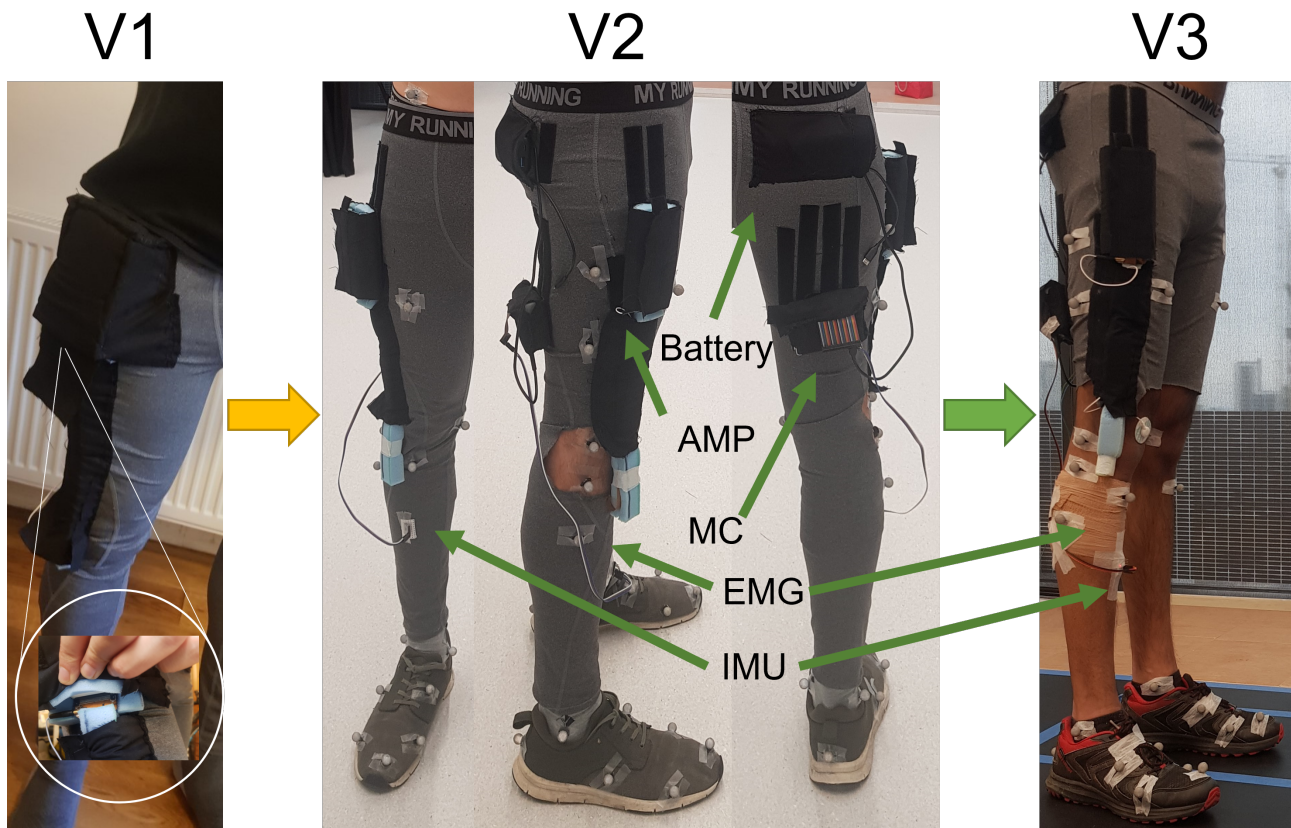


Figure 3.1: Illustration of iterations of the thermal garment design (AMP - EMG amplifier, MC - microcontroller).

URS 4 required the development of a novel custom HDEMG array. For this, the array's electrode contact points were embedded within a single layer of kapton, using a double-sided sticky foam pad to fix the grid to the skin, bringing the total thickness of the configuration to $\approx 0.7\text{mm}$. This is significantly thinner than the previous thickness of $\approx 1.2\text{mm}$. The cable routing was implemented at the front due to the smaller amount of cable sway and discomfort (compared to the back and side) reported by the user. During the treadmill gait study, I have tried different configurations for the participant with an amputation as he expressed discomfort from the cable that was pressed on the skin

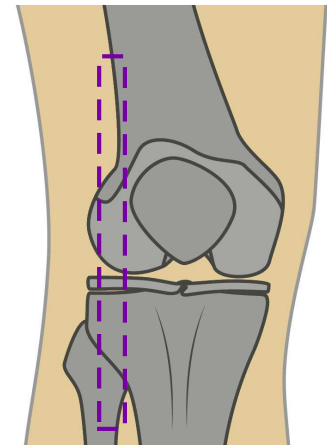


Figure 3.2: Custom HDEMG cable path illustration.

by his socket. Routing the cable from the back, it pressed mostly against soft tissue, which was quite uncomfortable during walking. Routing it from the front does press on the bone but

it was an improvement due to the little change of volume while walking, thus the discomfort was coming mostly from the initial fit. To address that, the current cable routing passes between the Gerdy's tubercle and the tibial tuberosity at the front of the knee (Figure 3.2) to avoid increased pressure and socket gap over the bones. The area without electrodes was also shrunk vertically and contained no foam pad, minimizing the surface area and volume over the tibial contact. In this way, the electrode was not significantly pressing on any bone or causing discomfort.

Finally, URS 5 was addressed by including electrode features that are to match anatomical landmarks, ensuring placement consistency between participants and experimentalists. The central notch of the grid (Figure 3.3) should coincide with the lateral end of the tibia and the top end of the rectangular grid should be right below the fibular head. Since there are only two features matching to two landmarks, with the rest of the electrode wrapping

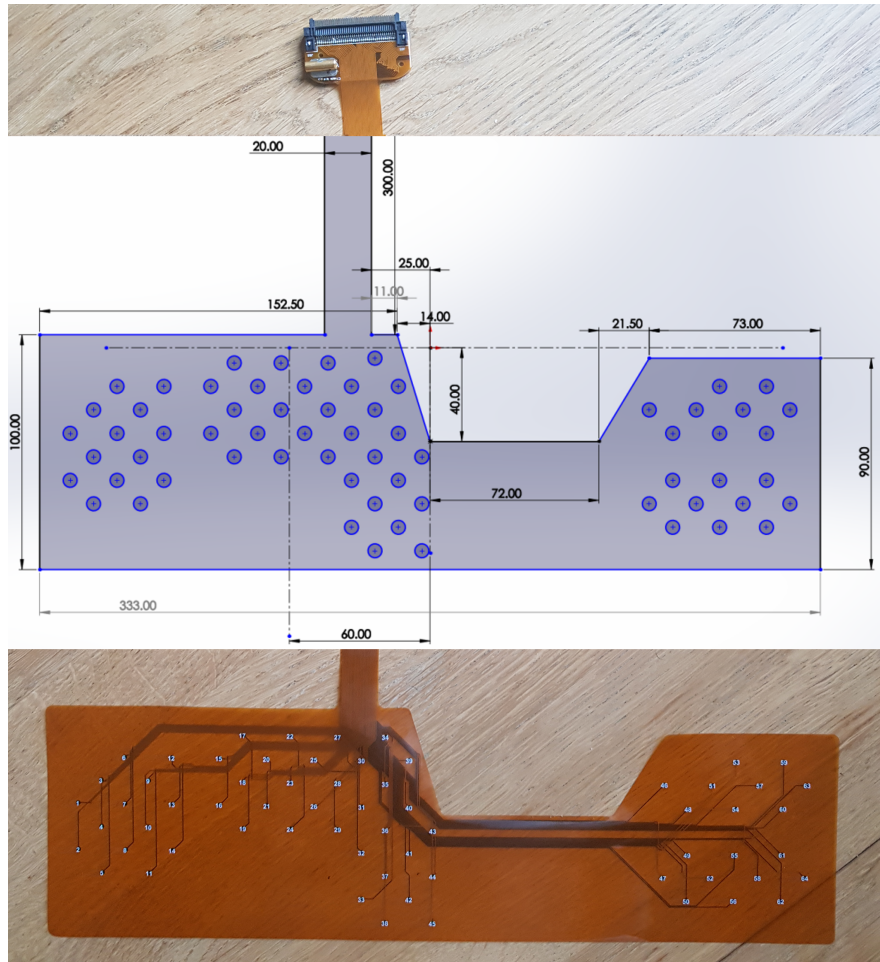


Figure 3.3: Custom HDEMG Electrode Design with dimensions.

ensure ease of use and placement for the experimentalist, and consistency in muscle coverage between participants (with the exception of the gastrocnemius discussed in the next subsection).

3.1.2 System Requirements Specification (SRS)

1. Universal electrode array - one-size-fits-all with minimal compromise on the gathered neural information and the coverage of muscle groups.
2. Minimization of movement noise.
3. Electronics allowing for prolonged use without compromise on the performance.

SRS 1 was challenging as it always involves a compromise between size, muscle coverage, and electrode density. The electrode density was limited by the capability of the wireless amplifier (maximum of 64 channels). Thankfully, this is more than sufficient, as the previous study conducted in Chapter 2 revealed no significance decrease in performance when the electrodes were reduced down to 24 channels (see Section 2.4). However, a compromise was made when it came to size and muscle coverage. To ensure that the electrode fitted the smallest size of shanks, its overall width was 33.3 cm (exact number due to electrode size and density). Due to its circumferential design and intended placement, the only difference in muscle coverage can occur at the gastrocnemius heads. However, this gap is not an issue since it is typically only up to a few centimeters, meaning that over 80-90 % of the muscle is covered, and the area between the heads has tendon tissue, which contains no extra neural information. Thus, since the neural information contained in the rest of the area is already captured at large, there is no significant loss and was deemed an acceptable compromise for the design. The complete dimensions of the array can be seen in Figure 3.3. The size constraint also introduced the need for optimization of the electrodes' location. As can be seen from Figure 3.3, the channels' pattern is irregular. The purpose of this decision was to not have any electrodes where they are not needed (over the tibia and soft tissues) and instead focus on the muscles. From previous experience I already knew that having a higher density over the tibialis anterior muscle is quite important, since it is the only surface muscle responsible for both dorsiflexion and foot inversion. On the other hand, there was no need to cover the entire area of the gastrocnemius muscles and is better to focus on the area that is stable over the muscle contraction (upper part of the gastrocnemius heads). Thus, the final pattern for the electrodes was set, using an inter-electrode distance of

2cm (again, due to size constraints).

SRS 2 was addressed by adding padding inside the EMG cable routing, which wraps around the cable, for motion noise reduction during locomotion.

SRS 3 included the addition of sufficient battery power given the use of the high performance components, which should provide at least 6 hours of continuous use (tested in Section 3.3).

3.2 Sensors & Prosthetic Integration and Mobile Application

While the aforementioned developments solved the practicalities of a uniform wearable setup, there needed to be software developments to enable the ease of use and flexibility of the prosthetic controller. The prosthetic foot intended to be used for embedding and testing the prosthetic controller described in Chapter 5 that was the device developed by Prof. Hugh Herr's lab at the MIT Media Lab. The specific prosthetic device is an actively powered 2 DoF transtibial prosthesis that is also capable of modulating the ankle joint stiffness. An earlier version of this hardware has been used in a previous study for prosthetic control [194]. At the time, this hardware choice was made due to it being the only device capable of 2 DoFs power modulation along with stiffness changes. We've established a long-standing contact with the Prof. Herr and were in constant exchange of information regarding the visit, the hardware and software used, and the participants' recruitment. We were informed that the microcontroller used to control the prosthesis was a Raspberry Pi and the software language was Python. Thus, the controller and computer language choices were based on this information. However, the prosthetic setup at MIT did not use either a Raspberry Pi or Python as a language for prosthetic control. Thus, further technical developments needed to be made for the implementation.

Below are lists of URS and SRS that pertain to the requirements needed for these developments and how they were addressed. The testing and results for these implementations are reported in Section 3.3.

3.2.1 User Requirements Specification

1. Ability to measure accurate and detailed acceleration and muscle activity data.
2. Wireless accessibility to controller for bi-directional communication, data and algorithm calibration visualization, and data recording.

URS 1 involved the software integration of HDEMG and high frequency IMU devices within the controller. Libraries for the wireless EMG amplifier and the IMU device were created in Python. Although I have previously developed code for the EMG amplifier in MATLAB, it required a lower-level control and a switch to a different language (see SRS 1 in the next subsection), thus this was created. The IMU, due to the novelty of the chip at the time, lacked any available code and all the classes were created from scratch using the device's manual for registers' information. This allowed not only its use but also adjusting settings and setting up the device as needed. This novel device was chosen, instead of other available ones, due to its high resolution and sampling rate, allowing for a match in sampling rate with the EMG (2000 Hz) at a resolution better than the rest.

A mobile application was created to address URS 2. This mobile application communicated with the controller wirelessly via Bluetooth, had a terminal console for sending and receiving messages from the controller, as well as included buttons for initiation and ending a data recording, data visualization, and disconnecting from the controller (see Figure 3.4). For visualization, the user was able to choose the type of data they wanted to be displayed as well as see an indication for data recording in progress and the elapsed time of said recording. Furthermore, an additional visualization was available in this plot for the algorithm calibration. Similar to the brief EMG data collection procedure for the 2DAPS algorithm described in Section 2.3.2, a visualization screen replicating this procedure is also available in the app. This was never used due to the longer computational time to train the algorithm using the available RaspberryPi, and the training was performed using the laptop. Nonetheless, it is available and can be used in the future if the training algorithm is optimized.

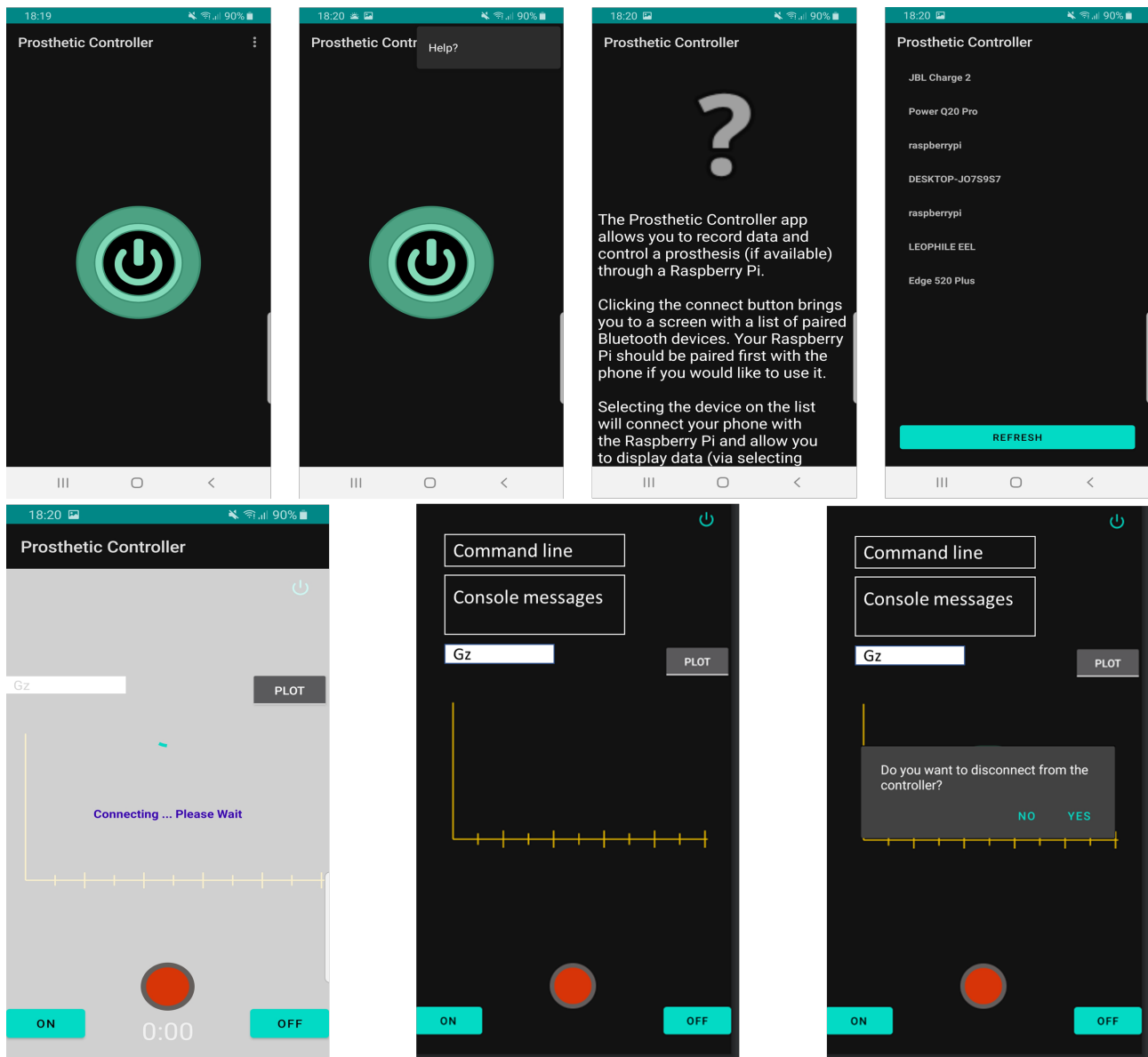


Figure 3.4: Mobile Application Layout. Tiles arranged from the start screen (top left) to the disconnect prompt (bottom right) with duplicate start and end screen illustrating the prompt from their respective bottom presses (three dots and switch-off button).

3.2.2 System Requirements Specification

1. Software language allowing for easy integration with the intended prosthetic hardware.
2. Prosthetic integration.
3. Closed-loop feedback control for 2DoF torque and position.
4. No inadmissible (longer than required transmission time) delays or any resulting data

loss.

5. No significant visualization delay without loss of visual information.

The software used for SRS 1 was Python due to the aforementioned information that the MIT prosthetic hardware is using it in their implementation. For the same reason I embedded the code in a Raspberry Pi 4B (4GB RAM), as this was their supposed choice of hardware. Thus, all of the legacy scripts were converted into Python and implemented on a Raspberry Pi.

SRS 2 was raised by the fact that the information about the used software language and hardware for the prosthesis at MIT was incorrect. In the original intention SRS 1 should answer all the requirements and SRS 2 would not be necessary. However, the prosthesis control was coded in C++ and used a different Linux-based microcontroller. Due to the complexity of converting the whole controller and all of its associated components from Python to C++ (the language the prosthesis used), an additional communication instead was built between the two systems. After multiple initial communication tests and system incompatibilities, a final solution was found involving adding and compiling additional kernel options for the serial communication in-between. Following this, the separate classes for communication in each respective language were created.

SRS 3 was needed for the conversion of the 2 DoFs torque control commands of the RaspberryPi to the low-level torque output of the prosthesis due to the transmission system. In short, the actuators' configuration is akin to a four-bar linkage system. As such, the sagittal plane torque is easily configured, as it is represented by the summation of the outputs of the two motors. The frontal plane, however, would be dependent on these changes in sagittal plane torque. Thus, a small feedback loop was devised for setting the frontal plane torque while the sagittal plane torque was kept constant. This feedback loop is working at 1000 Hz (10 times quicker than the torque update rates of the prosthesis) and does not influence or delay the next torque update. For the position, this is an easier problem since there is no interaction with the environment, thus it can be directly set without the need of a feedback loop.

SRS 4 was critical as any processing delays can result in transmission delays, which in term

will cause data loss or malfunction of the controller. This was addressed by: (1) writing data only once per recording and buffering the data during a recording on the random access memory (RAM) of the controller; (2) optimizing processing functions; (3) implementing parallel processing and kernel priority scheduling control (see next section for details).

SRS 5 involved addressing a couple of concerns on how to handle the data transfer without any losses and how to prevent significant display delays. The former was addressed by minimizing the size of the data sent from the microcontroller to the phone app. There were five data points sent from each individual plotting variable, apart from the EMG, in which case there were 20 data points (five per each channel, four channels). These five data points were data averages at every 20ms of the 100ms data window, thus five values. Furthermore, there is an additional buffer in the phone application that waits for a full set of data, as sometimes the data is sent in a truncated manner (i.e. first send three points and after a few milliseconds send the other two points). This buffer is set to 300ms, as the data delay is never larger than two data transmissions (200ms) and an extra 100ms were provided as a safety net.

The second concern is about data plotting delays. As the plots are in real time and, in the case of EMG, can display multiple lines, then a delay can be easily caused by the quick redrawing of the pixels on the phone screen. To avoid that, only low-level draw functions were used for maximal optimization of the pixel drawing. A plotting function was built from scratch, using the lowest level registers for display pixel drawing, where the pixels for the axis and axis labels were set as constants and the only live drawing was the line(s) that was updated on demand (initially set to all zeros). This allowed for no perceivable delay apart from the one in transmission due to Bluetooth interference (up to 200ms).

More information about the mobile application development is provided in the Supplementary Information section.

3.3 Microcontroller implementation and testing

3.3.1 Implementation

Lastly, all of the components of the section above, together with the algorithms from Chapter 2 and Chapter 5, were implemented into a Raspberry Pi microcontroller. As Raspberry Pi uses a Debian Linux kernel, which is not a real-time system, certain precautions needed to be made to ensure a tight execution priority control. For this, a pseudo real-time Linux kernel was installed on top of the Debian one, which allowed for a stronger priority control, in which the controllers Python script was set as the highest priority. Even though priority changes can still rarely occur, due to how the operating system functions on the lower level, these changes resulted in sub-millisecond delays, so they did not affect the overall controller execution.

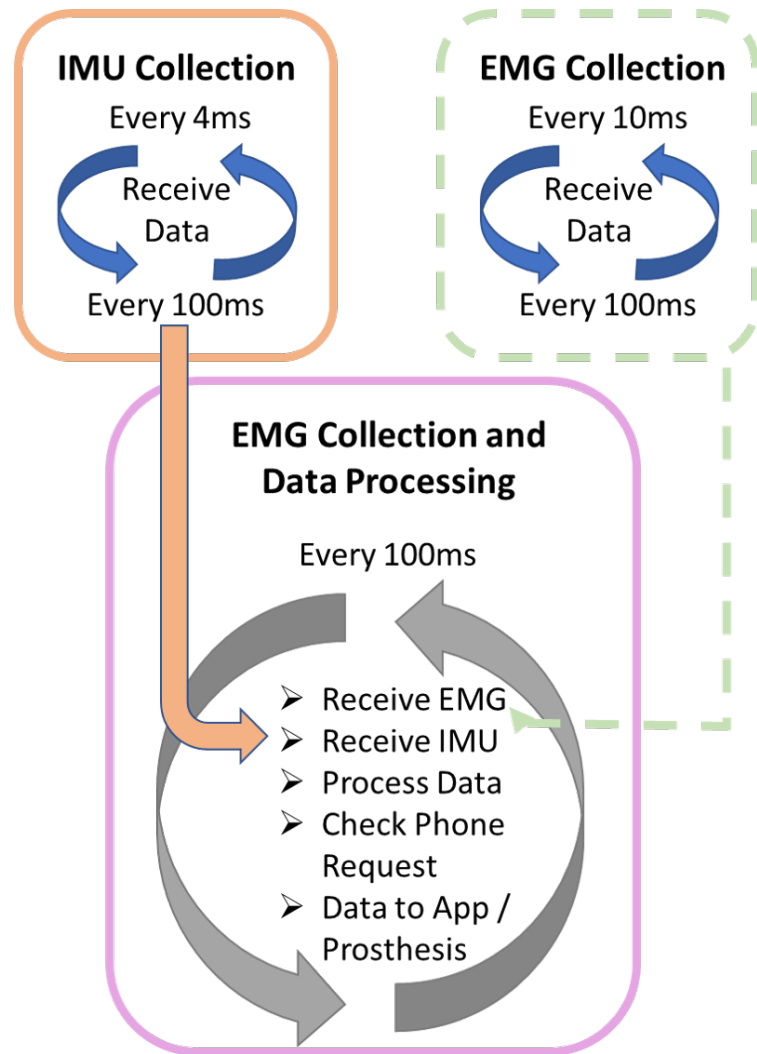


Figure 3.5: Controller Software Structure with separate processes signified by rectangular boxes and pipe communication between processes signified by an arrow (dashed). The dashed EMG collection process is used only in the SPI configuration of the software.

The overall software structure can be seen in Figure 3.5. It contains two processes, working in parallel and communicating with each other via software pipes. In Python, there are two ways to achieve parallel execution – multithreading and multiprocessing. Multithreading is an asyn-

chronous execution allowing for the triggering of commands/functions while another process is waiting and multiprocessing spins a whole new process instead. While multithreading is more resource efficient, it might cause data loss as a certain command/function execution might last longer than the data communication rate (2000Hz). As such, considering the computational resource overhead that the Pi allows, a multiprocessing was used to ensure this does not occur.

The two parallel processes were the IMU data acquisition and the EMG data acquisition and overall data processing. The IMU process communicates with the I2C-connected IMU device and continuously receives data at 2000Hz rate. This process is initiated at the first received EMG data window, thus synchronizing the two devices. The EMG data is acquired at 2000Hz but communicated every 100ms. As such, it sends 200 time samples of the 64 EMG channels (12800 samples in total) every 100ms. Thus, the IMU process collects 100ms of data and, once a full window is collected, it is sent to the EMG process. Since both processes are synced at the start, and the EMG communication is tightly controlled at the EMG acquisition board, there were no issues with data timing mismatch. This was further tested and validated by logging the CPU timestamps during data streaming and acquisition of both devices. It revealed that a slight difference can occur, but that is inconsequential as it was always below 5ms.

The EMG data acquisition and overall data processing part is executed every 100ms, which is controlled by the blocking EMG acquisition. This option was chosen as the EMG board uses a real-time embedded system with tight priority scheduling, thus the timing is better controlled. Once, EMG data is received, IMU data is also received, after which the binary information is converted into a float point format and reshaped into two matrices containing channels/axes and time sample points for 100ms of data. This data is further filtered and processed to provide predictions for 2 DoFs torque, position, and stiffness of the ankle, which can then be streamed to the prosthesis and/or displayed on the phone screen. The process also contains the phone's Bluetooth socket along with a listener, which is checked at the start of each data acquisition for messages, start/stop recording prompts, controller termination, or data display requests. To optimize data saving and avoid delays or losses, due to the memory overhead of the Raspberry Pi (4GB RAM), all the raw binary data is stored in memory and pushed to the SD card once the recording is complete.

Finally, when the controller was implemented in the prosthetic hardware at MIT an additional process (to the 3 processes seen in Figure 3.5) was created due to the fact that the RaspberryPi system is not directly in control of the prosthesis but uses an intermediate serial communication instead. This separate process was used for parsing the predictions made in the "EMG Collection and Data Processing" process into 10ms packages of data and sending them over via the serial port. The necessary update frequency for the other system was 100Hz, which is the reason for 10ms transmissions. For the other Linux-based system, a separate serial and prosthetic communication protocol was created in C++. The serial communication was configuring the low-level data transmission settings, parsing the received data and converting it into the format required, and passing back to the Raspberry Pi the prosthetic state (whether it was in stance or in swing).

In this configuration, the Raspberry Pi and the other Linux-based system communicated with each other via a serial connection. The low-level prosthetic control within the other Linux-based system consisted of obtaining the state and passing the torque/ angle and stiffness to the prosthesis. The state was determined from the foot's contact force and was initialized as stance. If the prosthetic foot's contact force during stance is under a certain threshold, then the state is switched to swing. If the foot is in swing and the foot's contact force is above a certain threshold, then the state is switched to stance. These threshold values were determined from previous work of the group and were provided. Thus, the Raspberry Pi predicts the torque/position and stiffness multiplier, transmits that through a serial port to the other device, which sets the desired torque/position and stiffness of the prosthesis, and reads and transmits the state (swing/stance) back to the Raspberry Pi. This communication occurs within five milliseconds.

3.3.2 Testing

All of these implementations and the final controller were tested in a variety of conditions inside and outside of the lab, to ensure consistent behaviour during different noise conditions. The controller's execution time was always less than 30ms, which allows for an even further reduction of data acquisition time interval if it is ever required. During the home and outside

environment testing, it was found that mains interference can be significantly larger than in a lab environment and an additional band-stop/notch filter was needed. In lab conditions this was never necessary as a common average filter was sufficient to eliminate mains noise. In much noisier conditions, however, this filter was not sufficient and a band-stop filter was implemented to eliminate the interference. As mentioned above, Bluetooth delays can also be observed at times, when there are a lot of wireless communication devices around. However, this was never more than 200ms and occurred only for data streaming (mostly of EMG) due to the large throughput.

An actual issue was observed for the WiFi EMG communication, which can interrupt for 1-2 seconds and can occur up to 5 times in a 10 minute interval. This is typically not an issue if only data recording is considered but is a major flaw for prosthetic control. That is why the WiFi EMG acquisition device was used only for data recordings, in which if data interruption was detected the recording was discarded. For the real-time prosthetic controller, an SPI-communicating EMG acquisition device was developed and used. This amplifier was developed in collaboration with the company providing the WiFi device, where the hardware requirements and firmware design were devised together and performed by the company, and the Python software was written by me. This device, due to its SPI communication, allowed for data transfers every 10ms, due to which it needed its separate multiprocess. Thus, the SPI version of the software had three multiprocesses in total instead of two (Figure 3.5). The only difference was that the EMG data was collected in that separate process and sent to the main data processing once every 100ms. Further testing and validation was done to ensure that both the WiFi and SPI versions were identical in terms of data quality and code execution time. Because the hardware for both of the devices was the same, with the difference being a lack of a WiFi module for the SPI circuitry, expectedly, there was no change of data quality. When it came to timing, both of the scripts performed identically and there was no difference in data transfer and code execution. The SPI module requires a small cable addition, which, similarly, did not affect the wearability of the device as the amplifier and the microcontroller devices were on the same thigh and does not affect the gait or pose any issues during use.

The prosthetic integration was also tested extensively for execution timing, data transmission

accuracy, and real-time practical issues. The values reported here are obtained from a continuous 20 minute recording. The final system passed all these checks with data values being identical between the systems and data samples time stamps difference staying below 3ms, which is well within the 10ms update interval. The controller was working reliably in real-time and only one minor practical change was implemented to avoid any complications. The change was concerning the accuracy of stance/swing length predictions. Because there could be a small discrepancy (tens of milliseconds) between the predicted and final length, if the prediction is shorter, it would mean no values for that phase. This was addressed by elongating the phase by decreasing by a small increment/maintaining the torque/position respectively. Thus, because, in reality, the torque towards the very end is decreasing, if the predicted stance phase is shorter, torque will be incrementally decreased further by a small value for the time mismatch (-0.5% from the sagittal torque and -0.25% from the frontal torque every 10ms). If the predicted swing phase is shorter, then the angle will be maintained, as there are very little changes in kinematics at the end of the swing phase. In general, as this time mismatch is not perceivable, these changes should not cause a significant difference in the controller's overall performance, although it would need to be further investigated.

And finally, the prosthetic controller was fully implemented and tested with the aforementioned active 2 DoFs prosthetic device from Prof. Herr's lab at MIT. The computational results achieved demonstrate an average computational time of <25 ms for the whole control loop (data acquisition, processing, predicting, communicating, and final prosthetic actuation). It is important to note is that this entire control loop provides predictions for 100 ms into the future, thus has an overhead of over 75 ms, which can be used for additional computations. On the prosthetic actuation side, the low-level control loop is outputting the signal within <5 ms, which is well within the 10 ms transmission updates.

3.4 Concluding Remarks

The successful incremental development, testing, and validation of all the components of the wearable setup presented in this chapter was a significant milestone for the project. The implementation of all of these elements, from custom garment and electrodes to mobile application and microcontroller integration, finally enabled the further comprehensive data collection and prosthetic controller completion detailed in the following chapters.

3.5 Supplementary Information - Mobile Application

The mobile application was written in Kotlin (app language) and built to be fully modular and up to the most recent standards of mobile app development. As such, it followed a structure of Fragment-View Model Factory-View Model and the associated layout for the visual design, ensuring low resource (CPU, battery, etc.) consumption. The importance in this structure arises from the fact that every time a view changes (i.e. screen rotation, redrawing of pixels, etc.) all the data is destroyed and re-created. The View Model Factory allows for data, such as the Bluetooth socket, to not be destroyed. However, it is still inefficient and insecure to keep the data externally in a view. Instead, wrapping and containing it within a View Model allows for a secure exchange of information between the microcontroller and the phone, while simultaneously optimizes the process by not destroying that information when a change of view occurs. In this scenario, the layout is a simple pixel drawing method, which is instructed by the View Model on what to draw and display but contains no information (it just acts as a drawing mechanism).

The final mobile application has two main activities, comprising of executing the Bluetooth connection and the data display and communication, along with two small activities that contain the tittle and the about page. The Bluetooth connection activity did not have a View Model Factory as it was the first instance after the tittle and about page, thus containing no data. Instead, it had a dynamic adapter for the list of paired Bluetooth devices, which can be refreshed in case a new device was just paired and is not showing on the list (top right tile

in Figure 3.4). How this activity works, in brief, is that it checks if Bluetooth is enabled and generates a list of information for the paired devices. It constantly listens for new pairings, and, in the case the refresh button is pressed, it adds a new device if needed. Once the desired device is clicked on, it switches the view to a waiting screen (bottom left tile in Figure 3.4) and attempts a connection. If successful, it passes the information to the other main activity, which is initiated. If the connection is unsuccessful, it brings the app back to its starting page.

The other main activity pertains to data display and communication. It has a View Model Factory since the Bluetooth socket information of the connected device is sent to that activity from the previous one and would need to be preserved. The created View Model by this factory, is secure and inaccessible by other functions, containing the data received from the microcontroller and the data that is to be sent to it. This View Model not only contains the raw data and does the processing, but also controls the functions that are executed when a button is pressed on the display. The associated layout to this model contains four buttons, a drop-down menu, a plot, a timer, and an LED indicator for recording status (blinking if it is recording) as seen in Figure 3.4. The ON and OFF buttons are for starting and stopping a recording. If the ON button is pressed it sends a start recording command to the microcontroller and starts the recording timer and the LED indicator on the screen. Similarly, the OFF button sends a command to the microcontroller to stop recording the data and stops the timer and the LED indicator. The shutdown button at the top right corner of the display is to turn off everything. Once pressed a pop-up prompt will ask if you are certain that you would like to disconnect (bottom right tile in Figure 3.4). If no is pressed, nothing happens, and it goes back to the previous screen; and if yes is pressed then it sends a command to the microcontroller to shut down and then it terminates the Bluetooth connection and goes back to the initial home screen.

If someone wants to plot data, they can do so by pressing the plot button, which will start displaying a line graph with the real-time data that is sent from the microcontroller. The plot displays 5 seconds of data updated every 100ms. The type of data to be displayed can be selected from the drop-down menu on top of the graph (bottom tiles in Figure 3.4). The plot variables include single axis IMU data (six options), four channels of EMG data (the ones over

the tibialis, two heads of the gastrocnemius, and the peroneal muscles), as well as the position and stiffness estimates given by the algorithm presented in Chapter 2. As mentioned previously, all this raw data is safely contained and processed in the View Model, and only the data array that we want to display is sent to the layout file for display.

The last functionality provided in the application is a command line and console, above the drop-down menu, which displays messages sent from the controller as well as allows for commands to be sent to the controller. The microcontroller messages provide status updates as well as warning and error messages if such occur.

Chapter 4

Comprehensive Gait Data Collection

Novel sensor technology enables new insights in the neuromechanics of human locomotion that were previously not possible. However, there is always a period between the emergence of technology and its widespread availability. The developments in Chapter 3 have finally enabled me to collect detail muscle activation and inertial data of the shank. This setup was used to collect comprehensive locomotion data, which will be used to train the final prosthetic controller in Chapter 5. Furthermore, I intend to publish this data set and make it available for everyone to access, along with the scripts used for the data processing. This chapter describes this dataset, consisting of high-density surface electromyography (HDsEMG) and high-resolution inertial measurement unit (IMU) signals, along with motion capture and force data, for the lower limb of 10 able-bodied adults during multiple locomotion modes. The subjects performed level-ground and slope walking, as well as stairs ascend/descend, side stepping gait, and stand-to-walk and sit-to-stand-to-walk, at multiple speeds. These data will not only be used for my controller’s development but can also be used for the development and validation of locomotion mode recognition and control algorithms for prosthetics, exoskeletons, and bipedal robots, and for motor control investigations.

4.1 Background and Summary

As elaborated in Section 1.4, the underlying neuromechanical principles of human locomotion are not yet fully understood. This gap has an impact on the development of control methods for prosthetics and robotics. Sensor technology play a critical role in the study of human locomotion. Recent developments in sensing muscle electrical activity (e.g., with high-density surface electromyography - HDsEMG) or body accelerations (e.g., high resolution inertial measurement units - IMUs), allow for obtaining a rich neurological and biomechanical data (see Chapter 1). However, currently there are no publicly available locomotion datasets, which include this advanced sensing. Thus, I needed to collect such a dataset for the development of my own prosthetic control algorithm. Furthermore, datasets of this type would provide new insights in basic principles of human locomotion and guide the development and test of control algorithms and rehabilitation targets for assistive and therapeutic robotic devices. This is important because rehabilitation robotic devices have been clearly demonstrated to help with mobility restoration, but results show that there is still a lot to be improved in these devices [291]. Similarly, lower limb prosthetic users can benefit a lot from improved devices, as described in the introduction of Chapter 1. In order to improve such devices, more people need to have access to data, which allows them to test different strategies. Furthermore, such measurements can be used to gain a better understanding of human locomotion in an effort to create superior models, which can help to improve the treatment and rehabilitation of other human movement disorders.

Data conventionally collected during human locomotion include kinetic, kinematic, and EMG. While usually these data are recorded for a few locomotion activities, it is important to provide datasets for a broad variety of locomotion modes and speeds. Human locomotion speed has been shown to be important when characterizing healthy and pathological gait [292, 293, 294], with gait speed directly linked to independence and quality of life in post-stroke patients [295]. Furthermore, activities such as stairs and ramps locomotion, side-stepping, and sit-to-stand-to-walk, are commonly used to evaluate gait, understand human biomechanics, and develop better neuromechanical models and control algorithms for prosthetic/robotic devices. This is why I

have collected data under all these conditions that is going to be used to test and improve the generalizability of my model as well as serve other people in their algorithm developments and studies of motor control and impairments.

Gait data sets including kinematics, dynamics, and, in some cases, EMG have been previously made publicly available [296, 297, 298, 299, 300, 301, 302, 303, 304, 305]. However, the number of activities, recorded signals, and/or data formatting limit the application potential of many of these datasets. Some studies report only data averages [301, 302, 303], or subject-wise averages [298]. This type of data cannot be used for training control algorithms or for investigating individual differences, but rather mostly for a reference comparison. Other studies have published the raw data but are lacking muscle activation information (i.e. EMG) [296, 297, 299, 300, 298] or have a narrow set of locomotion activities, comprising of level-ground walking at self-selected speed or a variety of walking speeds [298, 299, 300, 302]. A few recently published studies include EMG and use different walking speeds [305] and ambulation activities [304, 306], but none of these provides advanced EMG or IMU sensing or contain a full spectrum of locomotion activities.

Because of these limitations in previous datasets, here a comprehensive lower limb data set is provided, including raw motion capture marker positions, force plates data, high resolution 6-axis IMU, 64-channel HDsEMG covering all major surface muscles below the knee of the dominant leg, and gait phase timestamps along with anthropometric data on participants height and weight. The data was collected from 10 (5 male and 5 female) healthy able-bodied individuals during a variety of locomotion activities including: level-ground walking at slow, preferred, and fast walking speeds; stand-to-walk at preferred walking speed; sit-to-stand-to-walk at preferred walking speed; sidestepping to the left and right at preferred walking speed; stairs ascend and descend at slow, preferred, and fast walking speeds; and ramp ascend and descend using a 5° and 15° ramps at slow, preferred, and fast walking speeds. This dataset can be used for the development of control algorithms for lower-limb prostheses, exoskeletons, and bipedal robots, as well as studying and modelling bipedal locomotion and techniques for rehabilitation (i.e. model-based functional electrical stimulation).

4.2 Methods

4.2.1 Participants

This study was conducted on ten healthy subjects: five males, five females, age-range: 24-35 years, body height: 154-198 cm, body weight: 44.8-87.2 kg. None of the subjects reported any known locomotion, neurological or other health-affecting condition that could impact their performance. Age, sex, body height and weight, as well as IMU distance from the ankle and the knee (measured from the lateral malleolus and lateral condyle respectively) of each participant were reported in the data set. The experimental evaluations were approved by the research ethics committee at Imperial College London (21IC6941) and were conducted according to the declaration of Helsinki. Each participant was briefed and provided with an information form to inform them of the procedure and potential risks before engaging in the experiment. A written informed consent was signed by all subjects prior to their participation.

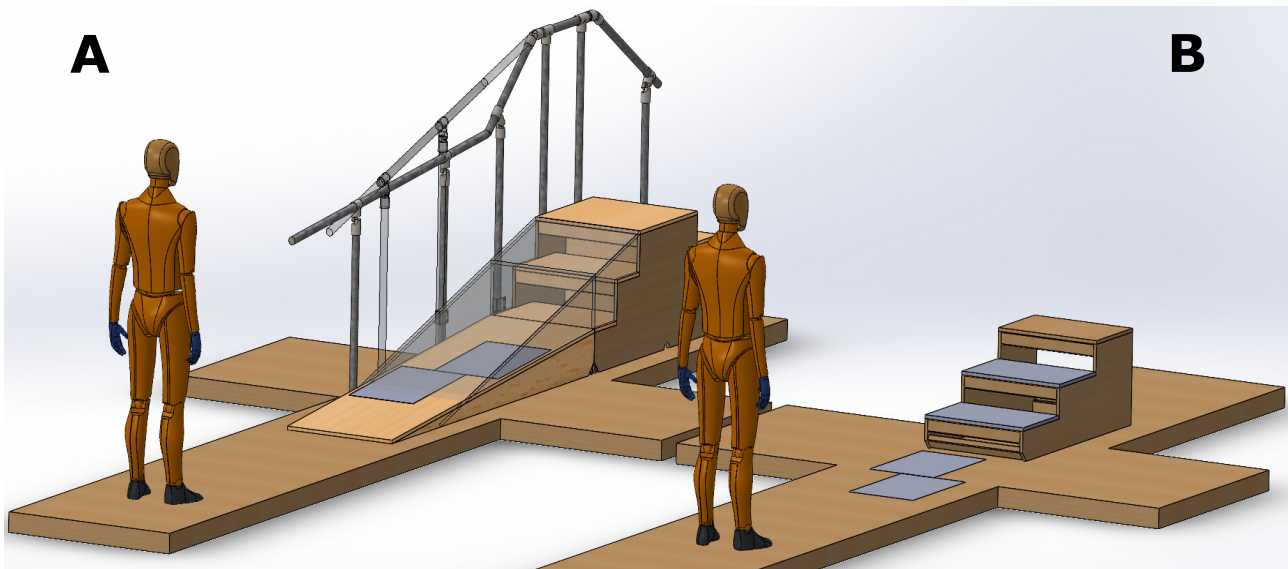


Figure 4.1: Motion capture lab rendering (to scale) with embedded force plates displayed in grey. (A) Ramp setup, where the solid ramp's incline is 5° and the transparent one (along with the rails) is 15° . Force plates were the same distance from the beginning of the ramp for both inclines and force plates on the 15° ramp as well as the rails on the other side were not displayed for clarity of illustration. (B) Level ground walking and instrumented stairs setup, where the instrumented stairs were removed from the volume when they were not used. Human dummy rendering courtesy of Gil P. de Paulo [307].

4.2.2 Instrumentation and participant preparation

Data were collected at the Musculoskeletal Mechanics laboratory in Imperial College London. 3D kinematic motion information of the lower body was captured via a 10-camera motion capture system (Vicon, Oxford, UK) sampled at 100 Hz. Ground reaction forces were recorded using two force platforms (Kistler, Winterthur, Switzerland) leveled with the floor, ramps, and stairs, and sampled at 1000 Hz. Motion capture lab details can be seen in Figure 4.1.

A 6-axis IMU device (ICM-20602, TDK, San Jose, USA) was used to record 3D acceleration and angular velocity and a wireless 16-bit A/D EMG amplifier (Sessantaquattro, OT Bioelettronica, Turin, Italy) was used for the EMG acquisition. Raspberry Pi 4B (Raspberry Pi Ltd, Cambridge, UK) was used for the EMG and IMU data collection.

The data synchronization between the motion capture system and the Raspberry Pi was done via a square wave voltage signal, initiated at the beginning of each recording.

Fully utilizing the developments described in Chapter 3, participants were required to wear the previously developed pair of custom tight thermal leggings (see Section 3.1). After donning the thermals, participants were instrumented unilaterally (on their right side) with the previously developed custom 64-channel HDsEMG electrode grid (see Section 3.1) and a 6-axis IMU sensor (Figure 4.2), both sampled at 2000 Hz and situated below the knee. The HDsEMG grid was vertically placed right below the fibular head, and was horizontally centered along the tibia. Before placement, the area of their right lower leg, where the custom 64-channel HDsEMG electrode grid would be placed, was shaven, exfoliated, and cleaned with alcohol. Subsequently, a 6-axis IMU was placed at the centre of the tibia, right below the HDsEMG grid (distances from the knee and ankle are provided in the data structures). Following the sensor placements, the EMG amplifier and the micro-controller with its battery pack were inserted in the slots created for them in the custom thermal shorts. Finally, motion capture markers were positioned on the skin above bony landmarks, secured via double-sided tape underneath the markers and medical tape at their base, in accordance with the modified Cleveland marker placement protocol [308]. The marker set consists of 35 retro-reflective markers (14mm diameter) covering the lower body.

Illustration of the complete participant instrumentation can be seen in Figure 4.2.

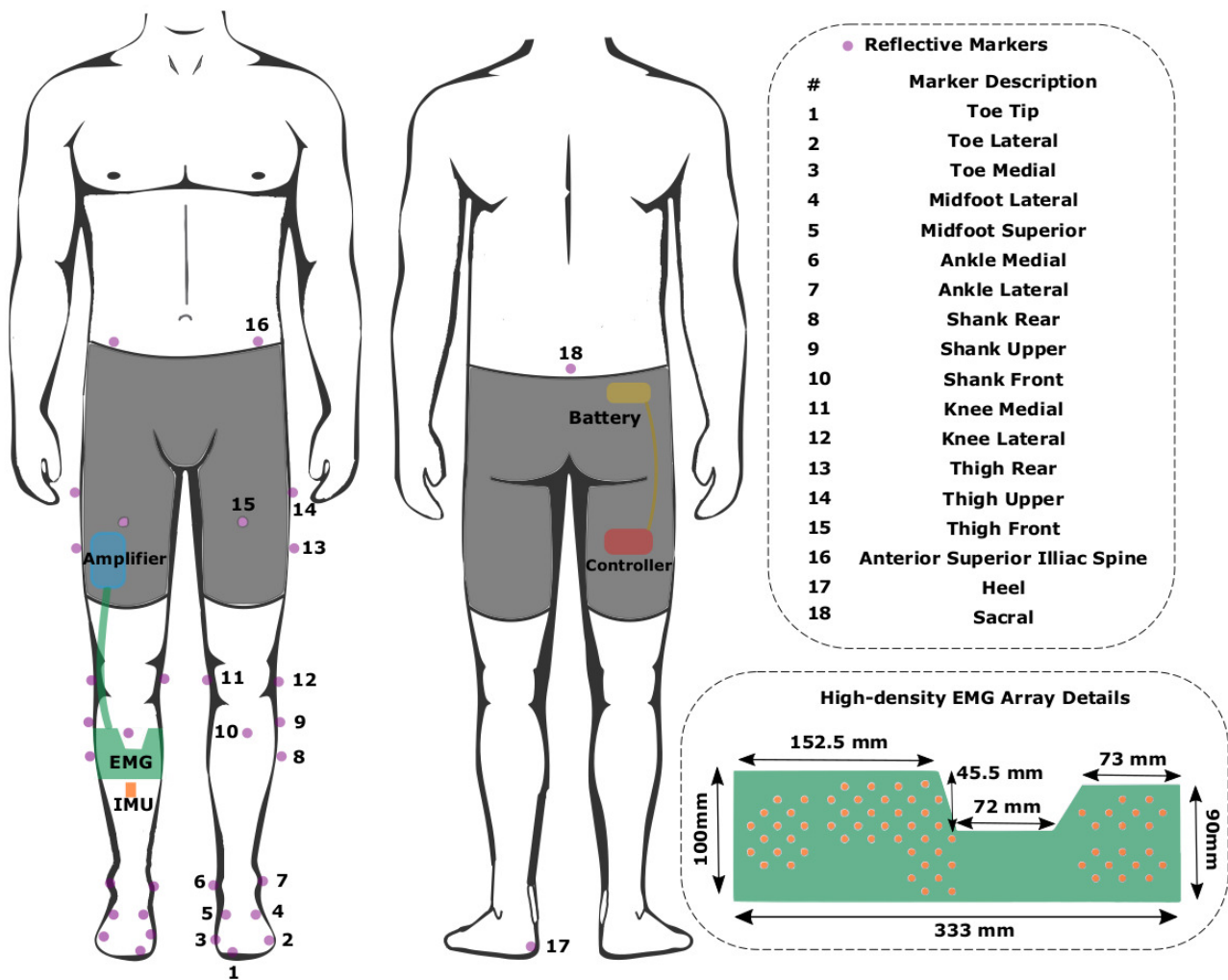


Figure 4.2: Participant instrumentation setup. Reflective markers (in purple) annotated only on the left side (apart from 18 - Sacral) as the right side is mirrored.

4.2.3 Experimental protocol

There were two acquisition sessions for each participant. The first session involved level ground walking activities and consisted of walking at different speeds, stand-to-walk and sit-to-stand-to-walk starting with the left or the right foot first, and sidestepping to the left and to the right during walking. The second session consisted of ascent and descent of stairs (170mm step height) and ramps (5° ramp and 15° ramp) at different walking speeds and ramp inclines. Each session lasted around three hours with the sensor placement and acquisition performed by the same investigator.

Before acquisition, each participant was briefed on the session details, after which they donned the custom thermal trousers used for housing the equipment. Following this, they were weighed and their height was measured, after which the equipment and markers were placed according to the procedure described in the previous sub-section. Finally, the distance from the bottom of the IMU to the lateral ankle malleolus and the lateral knee condyle was measured and recorded.

Motion capture static trial was performed at the beginning of session 1, and at the beginning of each ambulation mode (stairs, 5° ramp, and 15° ramp) for session 2. The reason for this choice was that the capture volume was kept the same but new equipment (stairs or a ramp) was introduced for the different ambulation modes; when an equipment was introduced in the set-up (stairs or a ramp), the cameras were re-calibrated and a new static trial was performed. For the static trial, the subject faced forward, with arms spread at 90° to the side, and remained motionless for the short duration of the capture. After that, the participants practiced walking naturally without looking at the force plates ahead, in order to avoid changing their walking pattern due to the position of the force plates.

After calibration and walking familiarization, gait trials were performed in the various conditions. Each condition was repeated three times for a total of 27 trials for session 1 and 54 trials for session 2. For each walking condition and speed, participants had practice trials in order to ensure a natural cadence and were encouraged to rest between conditions to avoid fatigue. Trials in which the participant's foot was only partially on the force plate or on both force plates were discarded and corresponding extra trials were performed.

4.2.4 Data Processing

Following the data acquisition, the motion capture data was labelled, gap-filled (when needed), and gait events were manually identified using force plate and marker data (Vicon Nexus 2.10, Vicon, Oxford, UK). Gap filling was performed using the cyclic fill, pattern fill or rigid body fill, depending on the gap length and gap position. Heel strike and toe-off were identified as the first sample and last sample, respectively, of the force plate contacted by the relevant foot or via the vertical position of the heel and toe markers, respectively, when there was no force

plate data. After this, the marker and force data were exported through the Nexus software as *.trc and *.mot files respectively and were filtered using a low-pass filter (second order zero-lag Butterworth filter, 20Hz cut-off frequency) in MATLAB R2018a (The Mathworks Inc., Natick, MA).

The marker and force plate data were further analyzed in OpenSim [309] using the inverse kinematics and inverse dynamics tools [310] to determine joint angles and moments of the lower body. OpenSim's musculoskeletal model Gait2392 was used in all the analyses. The collected static data and body mass were used to scale the model, applying scale factors and static pose weights to scale the body segments and adjust the marker positions. The scale settings used for each participant are also made available as part of the data set. Following the inverse kinematics and inverse dynamics calculations, all the data, including participant information, raw EMG and IMU, and time stamps for heel strike and foot-off, were segmented by gait cycle and arranged within a MATLAB structure. A total of 804 gait cycles for each side were analyzed.

4.3 Data Records

All data files were acquired without any identifier and will be published as such in FigShare under the terms of Attribution 4.0 International Creative Commons License:

<http://creativecommons.org/licenses/by/4.0/>.

Each file will be made available in *.mat format and represents a participant, with the naming convention being Pxx, where xx represents the participant number (01-10). Every MAT-file holds a structure, containing the respective participant metadata (Age, Sex, Weight, Height, IMU distance from the knee, and IMU distance from the ankle), left foot gait cycles, and right foot gait cycles. Left and right foot gait cycles sub-structures contain the gait cycles which start with the left or right heel strike on the force plate respectively. For each foot, the structure is sub-divided into types of walking, modes, and speeds as detailed in Figure 4.3).

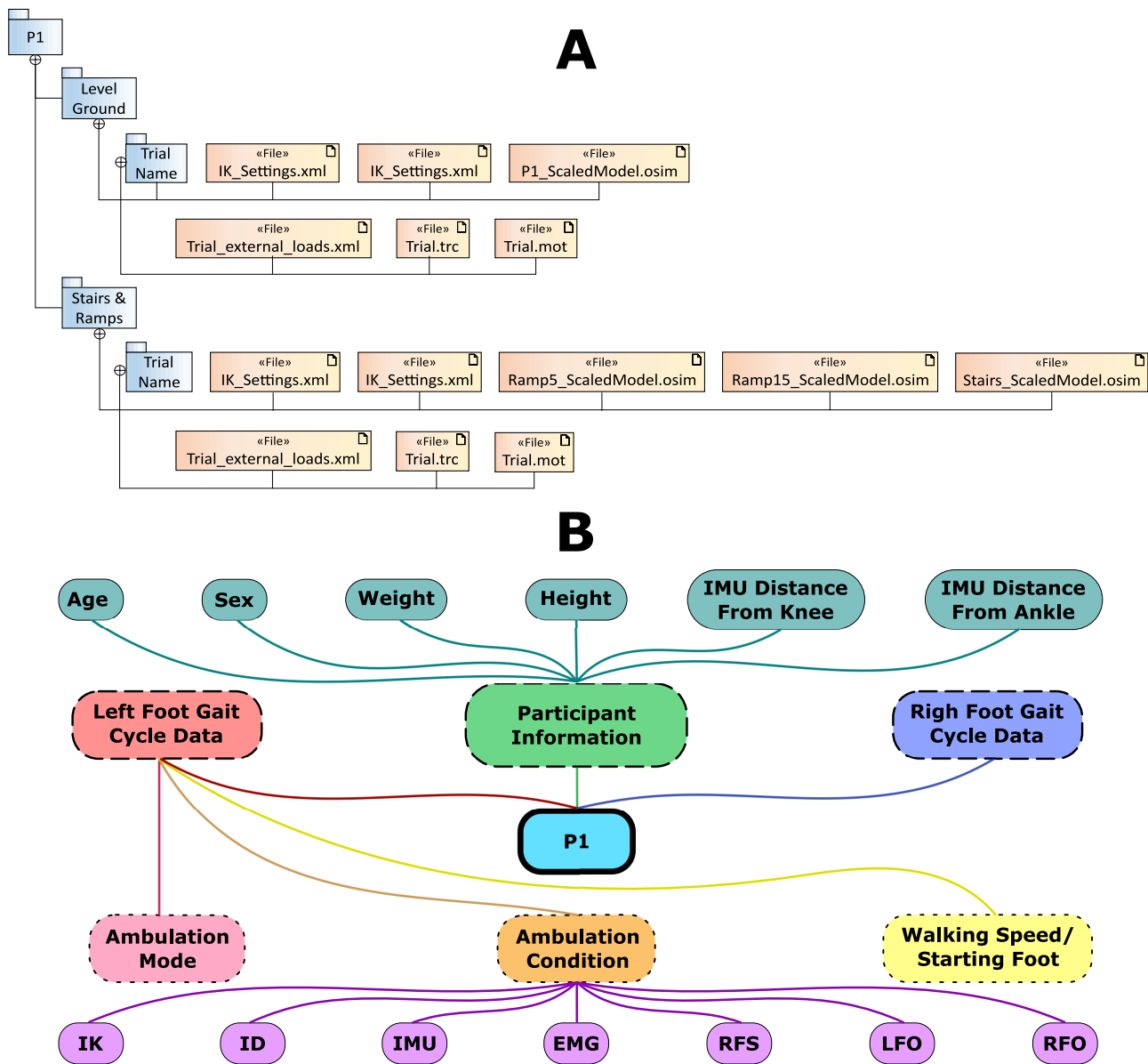


Figure 4.3: Data organization illustrating the folder structure (A) and the structured subject *mat data (B). Right foot gait cycle data has the same structure as the left one illustrated here, with the difference that instead of right foot strike (RFS), left foot-off (LFO), and right foot-off (RFO) timestamps, it contains the left foot strike (LFS), RFO, and LFO, as these are the timestamps of interest during a right foot gait cycle.

The data for each trial consists of raw EMG and IMU data, inverse kinematics (IK) and dynamics (ID), time stamps for foot-offs and heel strike during the gait cycle, as well as the respective trial name.

Furthermore, raw marker positions and ground reaction forces for all trials are provided in *.trc and *.mot format respectively (folder and file structure provided in Figure 4.3).

4.3.1 Data limitations

Due to the extensive recording sessions combining multiple modalities and novel sensor technology, the number and variety of participants was limited. Thus, the age range and number of participants would not allow for this data to be used as a general representation of the population. Additionally, due to the current channel limitations of wearable EMG amplifier technology, only one lower leg musculature could be instrumented, with the aim to work and improve that in the future to span all the muscles of the lower body. Trials for left foot start during the stand-to-walk level ground condition for participants P01 and P04 are missing due to an investigator error.

4.4 Technical Validation

4.4.1 Motion capture and sensor data

Motion capture system calibration was performed in accordance with the manufacturer's standard procedure at the beginning of each session, at each change of ground conditions (level ground, stairs, and different set of ramps), as well as in cases where a camera was externally perturbed by vibration/accidental contact. Both force plates were zeroed at the beginning of the session and at each change of ambulation condition through the Vicon Nexus software.

The reflective markers and EMG array were positioned by an electrophysiology and biomechanics expert via palpation of bony landmarks and muscle tissue in accordance to the marker set guidelines and the array placement procedure described in the methods section.

Capture volume and force plate data quality were inspected at each system calibration by asking the participant to perform movements and walk along the volume. EMG and IMU signals were inspected at the beginning of the session and monitored during the trials, ensuring that the quality was consistent throughout the recording session.

4.4.2 Data synchronization

Data synchronization was established via a cable between the motion capture and the sensor acquisition system. Motion capture was always initiated first, followed by the sensor data acquisition, which sends a voltage signal to the motion capture system at the start of sensor acquisition. After this, a trial can begin. At the end of the trial, the trigger is stopped followed by a termination of the motion capture trial. This trigger was visually inspected for every trial, ensuring the correct timing of the start and end of the trigger. Timing tests were performed before the study, to ensure the synchronization's reliability. Furthermore, there was never a mismatch between the lengths of recordings of the acquisition systems, which were inspected after each session.

4.4.3 Kinetic and kinematic data

The model used for inverse kinematics and inverse dynamics computations has been previously validated, showing average inter-examiner variability of 2.38° in joint angles and 0.33 BW in muscle forces and maximum of 0.33 BW variations in joint forces [311]. Another study investigating variability due to parameters reported changes between 2.7° and 6.4° for joint kinematics and 2.7 to 8.1 Nm differences in joint moments [312]. These differences are consistent with other models used in the field [313, 314, 315]. The inverse kinematics and inverse dynamics results, as well as the foot events, were investigated for each trial, ensuring their correct execution. An additional check was made for the following subject-structured data, which ensured that the trials were structured and separated by gait cycle correctly.

In the joint angles and moments data presented below (Figure 4.5 and 4.4), positive values of sagittal plane angles represent ankle dorsiflexion, knee flexion, and hip flexion, and positive values of sagittal plane moments represent ankle plantarflexion, knee extension, and hip extension.

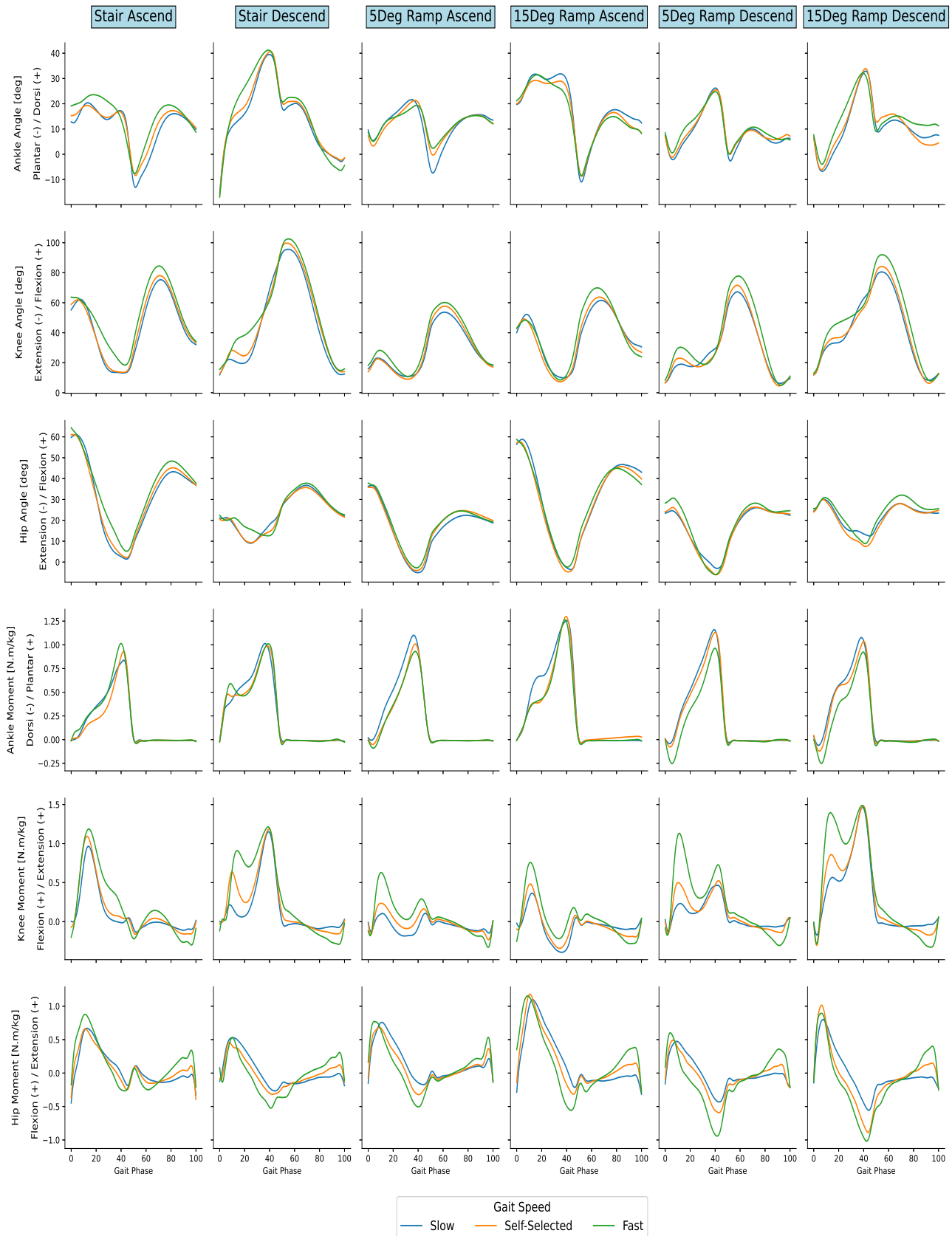


Figure 4.4: Joint angles and moments during stairs and ramps ambulation. Gait cycle duration normalized between two consecutive heel-strikes of the same leg and moments normalized by the respective subject bodyweight. Tiles at the top annotate the ambulation mode.

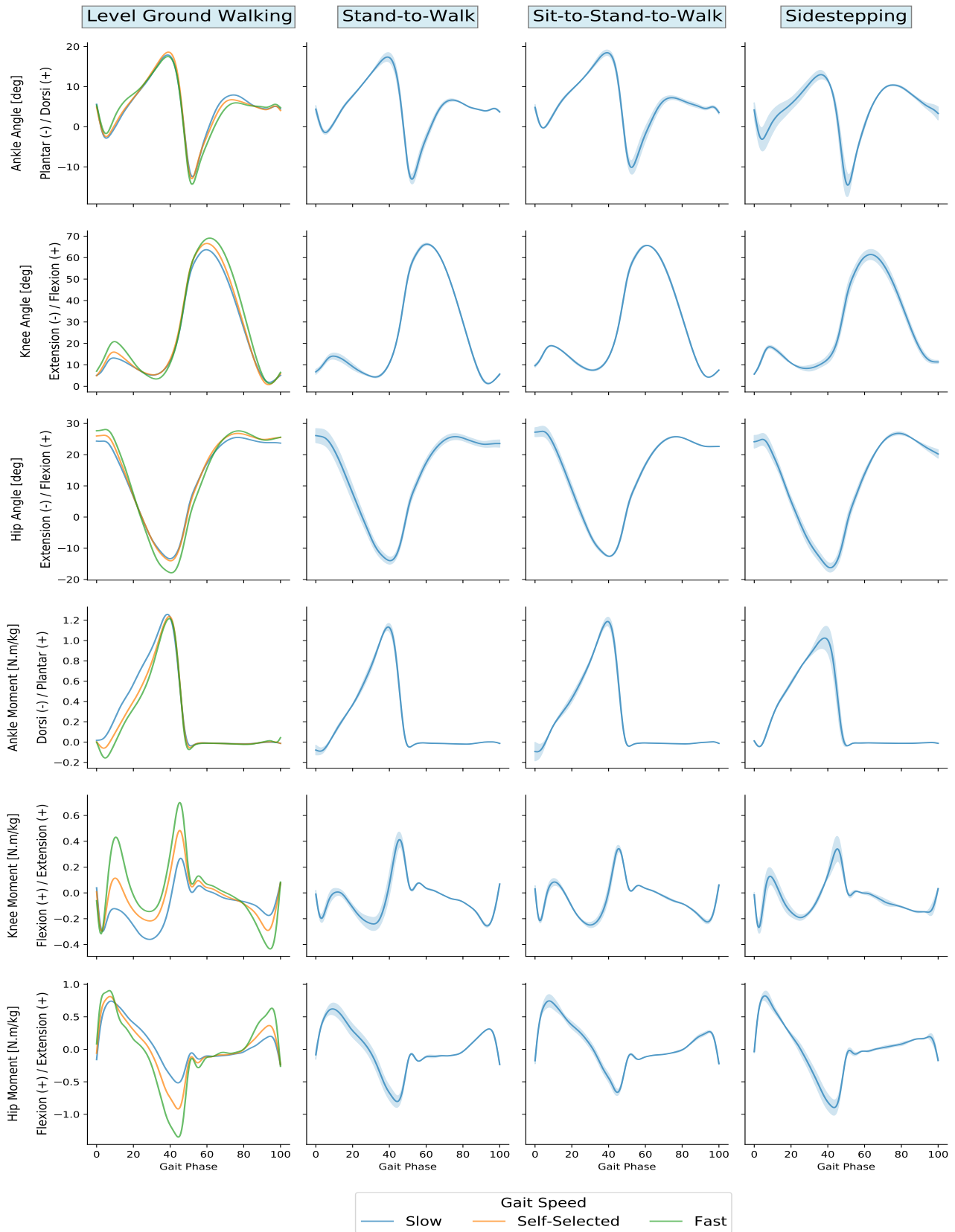


Figure 4.5: Joint angles and moments during level ground walking. Gait cycle duration normalized between two consecutive heel-strikes of the same leg and moments normalized by the respective subject bodyweight. Tiles at the top annotate the walking condition. The sidestepping plots are for the foot that is in stance during sidestepping. Shaded area for the stand-to-walk, sit-to-stand-to-walk, and sidestepping represent the standard deviations for the data due to starting with the left or the right foot or sidestepping to the left or the right.

4.4.4 Comparison with other walking datasets

Due to unavailability of a single data set that captures all the activities recorded in this study, the validity of this data set was assessed by comparing the angles and moments results to two other public data sets that together include all the activities measured in the current study. To compare sit-to-stand along with stairs ambulation and level ground, we used the data presented by Reznick et al. This dataset population includes healthy participants of mean age of 30.4 years (± 14.9), which is comparable to the population of the current data set (mean $\pm$ SD age: 27.2 ± 3.2 years). The walking speed selected for comparing level-ground data was 1.8 m/s , which is the closest equivalent to fast walking speed in young adults [316] and was compared to the fast-walking speed data collected in our study. Likewise, the stair step height and ramp incline used for the comparisons were the ones closest to our setup - 6.38in step height (6.69in/17cm in the present setup).

To assess side stepping along with all the rest of the activities, without sit-to-stand, our results were compared with the ones presented by Camargo et al. This data set population is also similar to ours (mean $\pm$ SD age: 21.4 ± 1 years). Conditions, which did not use walking speed variations were compared to the normal walking speed data. The ramp inclines used for comparison were 5° and 18° , which were closest to our setup (5° and 18°); and the step height used was 17.8cm, which was the closest to our step height of 17cm.

We computed a cross-correlation coefficient (XCOR) between the average curves of our data set and the others. The results demonstrated a high correlation between our data and the rest, with mean ($\pm$ SD) XCOR values of: $0.98 (\pm 0.02)$ and $0.82 (\pm 0.16)$ for level-ground walking angles and moments respectively; $0.96 (\pm 0.03)$ and $0.94 (\pm 0.03)$ for stair ambulation angles and moments respectively; and $0.92 (\pm 0.09)$ and $0.93 (\pm 0.07)$ for ramps ambulation angles and moments respectively. Furthermore, the increase in joint torque as the walking speed increases, which was observed in the other data sets matches with our results as well.

4.5 Usage Notes

A MATLAB script (`mean_gaitcycle_plots.m`) will be provided in FigShare to assist with plotting and utilizing the data. It demonstrates how to access different sections of the MATLAB structure and plot variables from them. It also provides an example of how to normalize gait cycles and plot their mean and standard deviation for a set condition.

4.6 Code Availability

The code for computing joint angles and moments will be provided alongside the data in FigShare. The script uses OpenSim tool plugins to run the inverse kinematics and inverse dynamics through MATLAB and generate a folder containing "*ik.mot*" and "*inverse_dynamics.sto*" files for the joint angles and moments from the inverse kinematics and inverse dynamics respectively. The code will be accompanied by a README file describing these details and its usage.

Chapter 5

Prosthesis Control Design and Evaluation

Drawing inspiration from vertebrate locomotion principles (see Chapter 1.4), ever since the inception of the neural controller (Chapter 2), the idea was to have a cyclical algorithm, which receives input from this neural controller and changes its behaviour in accordance to the user's intent. This is akin to vertebrate locomotion, which incorporates rhythmic circuits in the spinal cord that receive input from both peripheral sensory afferents and supraspinal commands from the brain to produce the final pattern of locomotion, which is adaptable to environmental changes (i.e. surfaces, inclines, ridges) as well as the animal's desires (predation, evasion, foraging, etc.). This final chapter will build upon the work presented in the previous chapters by developing the automatic oscillatory part of the algorithm, combining the previously developed neural algorithm with the oscillatory algorithm, and validating the performance of this complete controller using the previously collected data as well as demonstrating the complete prosthetic integration.

5.1 Introduction

Currently, one of the main challenges for user-driven prostheses is their control rather than their hardware [317, 318, 172]. While it is true that weight optimizations are needed when it comes to powered actuation, their torque/position modulation capabilities have far exceeded users' needs. In active lower-limb prosthetic control, the main challenge is that the algorithm needs to not only be extremely adaptable, providing adjustments for different speeds, terrains, and ground conditions, but also extremely stable and accurate. The sheer number of steps that each of us is taking every day, means that an error in even 1 % of the steps would result in more than tens (or even hundreds) of mistakes. Depending on the timing, these errors can cause falls resulting in further injuries, which would then be as a result of the choice of prosthesis. Thus, when offering an active prosthesis, one needs to make sure that the controller, even at its worse, will perform at least as well as a passive prosthesis; otherwise it just introduces an unnecessary risk to the user. Another big obstacle is addressing long-term effects of prosthetic gait, which are typically expressed in knee/hip pain [12, 243], back pain [244, 181], and osteoarthritis [15, 243] due to gait asymmetry [236, 237, 238]. Thus, the overall objective for prosthetic control is both optimizing the day-to-day performance and minimizing the long-term detrimental effects.

Passive prostheses are providing a very reliable and predictable performance but they lack the capability to reproduce biological gait [18, 19, 235], which results in long-term complications. Their active counterpart, while having the ability to provide sufficient power and showing some promise [22, 250, 251], are reliant on their controller, for which an optimal solution that consistently outperforms passive prosthesis is still missing [252, 254, 255, 241, 319]. There are many ways to resolve that task, with researchers in the past modelling tibia angles [256], damping [191], impedance [183], or reflexes [181], utilizing sensor data from IMUs, joint encoders, or potentiometers to determine the prosthesis' desired state. These models can be gait phase dependent (individual controller for each state) or gait phase independent (using a single controller), but none of them have managed to successfully capture the individual's locomotive variation, which require coordination with user's intent. The main reason for that is the controller's autonomy with respect to the user.

One way to change that is to implement a direct user input into the controller, which instantly captures the user intent and provides personalised behavior that reduces compensatory movements due to mismatch between desire and output. Some researchers have tried to do that via detection of residual muscle activity (using EMG) as it provides access to input from the sensorimotor system. There are two main approaches that people have taken for EMG control implementation - 1) utilizing EMG for locomotion mode recognition and associating prescribed movement with each mode or 2) using the EMG information as a direct continuous input to the prosthetic state. In general, the former approach provides a more predictable behaviour but is unable to provide user variability within a locomotion mode, while the second one is capable of this but is harder to stabilize and provide consistent behaviour. Furthermore, locomotion mode recognition approaches are hampered by the exponential nature of locomotion class definition - how much difference in locomotion justifies an additional class. On the opposite site, it is still an open question whether the information from the EMG is sufficient for providing consistently reliable input for continuous modulation and is it generalizable between people.

The limitations of locomotion mode recognition approaches due to class definition and their inability to provide within-mode variations was the reason to choose a prosthetic controller approach that utilizes a direct EMG input. My previous work in Chapter 2 informed me that I do have the necessary information to provide continuous modulation of position and stiffness during voluntary contraction and gait. This algorithm will be employed to modulate the automatic component of the controller (consisting of adaptive oscillators), physiologically inspired by the manner spinal rhythmic circuits are modulated by supraspinal neural input during vertebrate locomotion (for more information, see Chapter 1.4). Inspired further by vertebrate principles of locomotion, these patterns are gated by a simple phase reset reflex to provide fast modulation in case the foot is perturbed by an obstacle.

5.2 Methods

The controller presented in this chapter (Figure 5.1), represents the mid-level control of a hierarchical control approach, the concept of which was presented in Section 1.6 (Figure 1.5). It implements a continuous modulation with the least amount of gating in conditions. However, some of that is necessary due to the nature of the problem, which entails a switching in behavior (cyclic vs non-cyclic) and changes in resolution (torque changes in stance vs swing). Thus, switching of controllers for stance and swing phase of the gate as well as for no loading conditions, standing, and walking is included. This represents the high-level control (Figure 5.1) of this overall prosthetic controller. When used, the controller detects the user's intended activity (voluntary movement, standing, or locomotion). Depending on this, it will not use any oscillatory circuits (during voluntary movement) and increase the stiffness to the maximum (during standing), or it will use all the control elements and allow for stiffness modulation (during locomotion). The stiffness switch is due to the fact that there are changes in stiffness during standing without muscle involvement, which is what the algorithm relies on for a stiffness signal. And the non-existent use of CPG-like elements during voluntary movements is the reason for not using the oscillators during that time. Furthermore, during locomotion, large changes in foot position occur with minimal changes in torque, thus controlling the position allows for better control resolution.

This is why the controller implements a switch in behavior between stance and swing. As such, it detects whether the user is in stance or swing, and provides either modulations in torque or in position respectively. The low-level controller, for monitoring and modulating the actual prosthetic output (torque/position and stiffness) was mostly implemented previously by Prof. Hugh Herr's group. However, there were additions implemented due to the inclusion of a second DoF, which were described in Section 3.2.2 SRS 2 and 3. The whole prosthetic controller runs in an open-loop control scheme, apart from the low-level, which, as mentioned, has a closed-loop proportionalintegralderivative (PID) feedback scheme, making sure that the torque/position set by the mid-level control is the one that is physically outputted by the prosthetic hardware.

The rest of the section focuses on all of the individual elements of the controller, how they

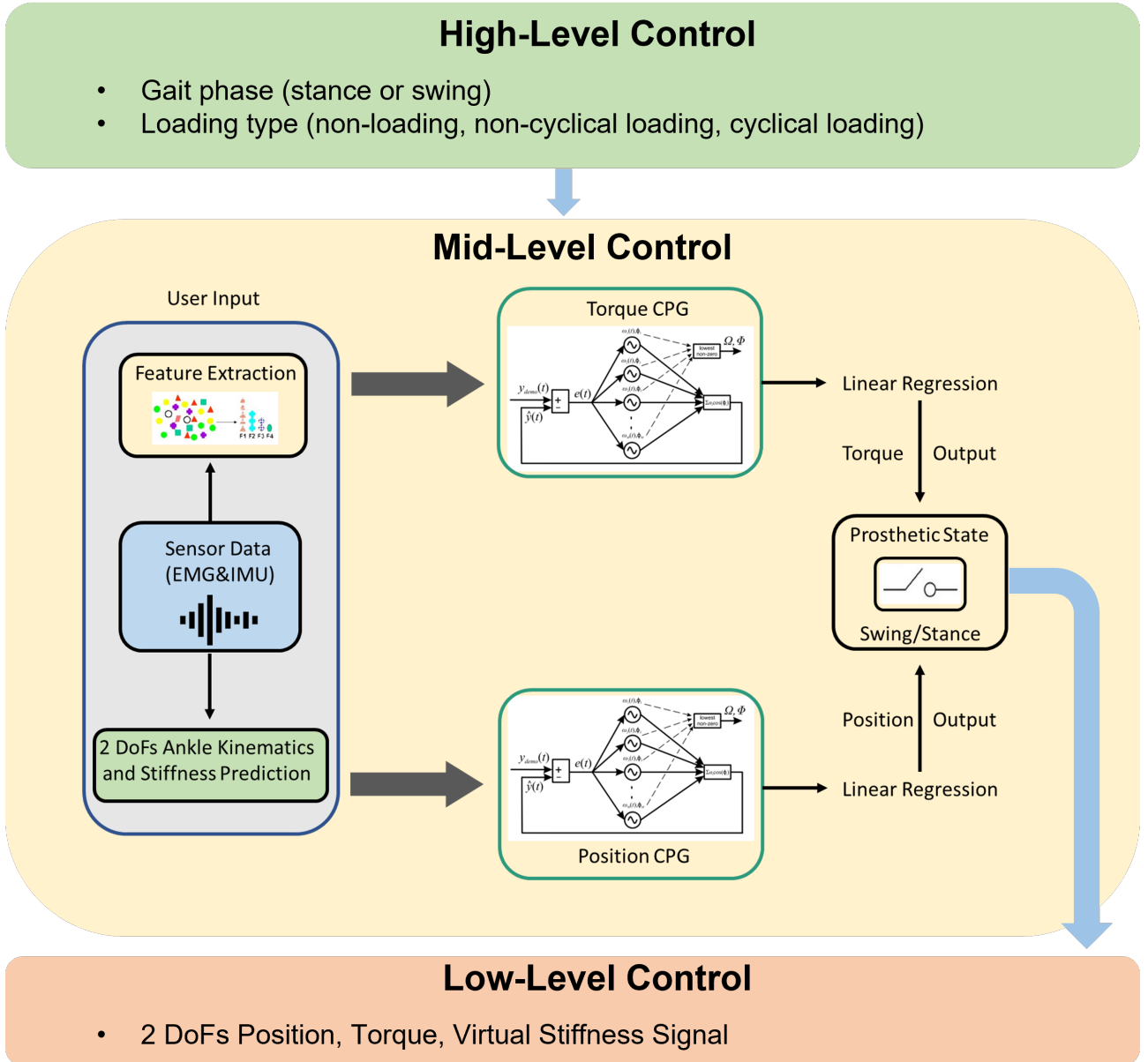


Figure 5.1: Hierarchical Prosthetic Controller Flowchart. The mid-level control illustrates only one DoF, but the structure is the same for the second DoF.

are selected, trained, and implemented, as well as their interactions that provide the final modulation of the prosthesis.

5.2.1 Adaptive oscillators

Mimicking CPG behavior can be performed in a couple of fundamentally different ways - either by constructing a neuron based model or a nonlinear oscillator system. Due to the complexity and number of parameters that are required for neuron based models and the simplicity of

behavior that is needed for transtibial prosthetic oscillations, neuron based models were not chosen as an avenue for this project.

Nonlinear oscillators are an extremely useful engineering tool, especially due to their ability for dimensionality reduction of control problems. This is because of their property to output complex multidimensional patterns by using a small number of scalar parameters. Moreover, they share all common features of structurally stable dynamical systems, providing smooth adjustments and transitions under parameter changes. This preserved structural stability allows for input fusion while maintaining the system's dynamics. Another critical property is their limit cycle behavior, which produces stable rhythmic patterns. All of these features make nonlinear oscillators very desirable for locomotion modelling and were the reason why they were chosen to be part of the prosthetic controller presented here.

There are many different models of oscillators with a varying degree of parameters, limit cycle shape, interconnectability, and temporal characteristics. One of the most widely used types is a Hopf oscillator [320, 321, 322], due to its simplicity and well-described behavior. It is based on the Hopf bifurcation (limit cycle appearing at the transition between stable and unstable states) and consists of six tuning parameters and a fixed radius for its limit cycle shape, with convergence time varying with the frequency (and magnitude) of the oscillations. Another simpler variation of the same kind of oscillators (harmonic oscillators) is the phase oscillator [323], which has only three tunable parameters, a similar limit cycle, and adapts quite well to input of varying frequency.

An alternative to harmonic oscillators are relaxation oscillators. These oscillators have two distinct oscillation phases, so when the system approaches stability (relaxation phase), a threshold is passed and the system is disturbed, moving further away from stability (disturbed phase) and restarting the oscillation. The relaxation phase is very long and defines the oscillation time as the disturbed phase is instant. An example of this family of oscillators is the Van der Pol model, which is described by a second order differential equation (can be converted into two first order differential equations). It has six tunable parameters and a varying limit cycle (dependent on the parameters). One main drawback of the oscillator is that under certain

conditions there is a change in frequency without a change in the frequency parameter (ω). Furthermore, the changing shape of relaxation oscillators is also undesirable in the prosthetic control application, which is why they were not the selected model candidate.

Due to their small number of parameters and large choice of input frequencies, phase oscillators were chosen as the main model for the production of rhythmic patterns. One drawback of such a system in general is their inability to dynamically adapt their parameters as they have fixed intrinsic frequencies. In order to overcome this drawback, expressed in lack of synchronization outside their phase-locking region, I have added an adaptive rule developed by Righetti et al. [324] to enable adaptation to a variety of complex rhythmic inputs and changes in their frequencies. Such oscillator has previously been used for frequency detection [323], and I have implemented it here for reproducing stereotypical oscillations of the ankle during human level-ground walking. In particular, the rhythmic patterns required were for sagittal and frontal plane torque during stance and position during swing, thus four different oscillatory systems.

As stated before, this type of oscillator has three tunable parameters, and is governed by the following equations:

$$\dot{\phi}_i = \omega_i - Ke(t)\sin(\phi_i) \quad (5.1)$$

$$\dot{\omega}_i = -Ke(t)\sin(\phi_i) \quad (5.2)$$

$$e(t) = y_{input}(t) - \hat{y}(t) \quad (5.3)$$

$$\hat{y}(t) = \sum_{i=1}^M \alpha_i \cos(\phi_i) \quad (5.4)$$

$$\dot{\alpha}_i = \eta \cos(\phi_i) e(t) \quad (5.5)$$

where K is the coupling strength, ϕ_i is the phase of oscillator i , $e(t)$ is the error input to the oscillators, y_{input} is the input signal, $\hat{y}(t)$ is the oscillators outputs' weighted sum, M is the number of oscillators, α_i is the amplitude associated with the i -th oscillator, and η is the learning constant.

The chosen values for these parameters were as follows: (1) a learning rate (η) of 0.8; (2) a coupling constant (K) of 0.2; (3) five oscillators (M1) for the torque patterns in both sagittal and frontal planes, and four oscillators (M2) for frontal plane position pattern and two oscillators (M3) for the sagittal plane position pattern. The learning rate and coupling constant have a complimentary action when it comes to convergence time (the larger the values the faster it converges) but they do have a different effect on the parameters. While the learning rate affects the amplitude oscillations, the coupling constant affects frequency ripples (larger value $\rightarrow$ larger ripples). Thus, because the larger learning rate was not affecting amplitude oscillations much, but the frequency ripple effects from a larger coupling constant (K) were significant, K was reduced to a minimum (0.2), while η was set at 0.8 (it allows for values up to 0.9 before resulting in deterioration of the reproduced pattern). Values below that for K resulted in lack of convergence while values above that were generating significant ripples. The number of oscillators varied mainly due to the complexity of the pattern - the more difficult it was to reproduce $\rightarrow$ the more oscillators were used. Thus, the lowest number of oscillators, capable of reproducing the sagittal and frontal patterns were chosen as specified above. The oscillators were trained on the level ground self-selected walking speed trials collected beforehand (see Chapter 4). The system was also compared to other types of oscillators (Hopf and Rayleigh), to evaluate the oscillator type decision, with the test revealing no significant difference in the produced patterns. One modification done to the oscillators for the real-time implementation was to inject replay converged values of $\dot{\phi}_i$ during oscillators' use without any input. This was done due to occurrence of a small drift in amplitude, which accumulates over time and results in larger errors during prolonged use. Thus, 3 seconds of the variations in $\dot{\phi}_i$ after the oscillators have converged were saved and later added to the live signal to prevent this drift.

5.2.2 Algorithm fusion and stiffness control

The overall prosthetic controller output of torque, position, and stiffness was provided by the oscillatory input described above, which was modulated by the developed 2 DAPS algorithm [233]. Due to the desirable intrinsic properties of the developed oscillators described above,

gait speed modulation was provided mostly by frequency modulation of the oscillators. This was done by scaling the frequency term of the oscillators proportionally to the predicted length of the gait phase.

Apart from the overall gait speed modulation, changes due to the user's input were provided in the form of amplitude changes to the oscillations by signals from the EMG, IMU, and ankle position and stiffness estimates. The choice of how to implement this input was explored via a linear regression and a Gaussian processes algorithm to determine whether a non-linear approach (Gaussian processes) is beneficial when considering the combination of these signals (oscillations and sensory inputs). The input to both classifiers were: (1) standard deviation of acceleration data (z-axis only) and angular acceleration (x-axis and z-axis); (2) mean absolute value of four EMG channels (the ones over the tibialis anterior, peroneal, and both gastrocnemius muscles); (3) predicted kinematics of the respective plane; (4) adaptive oscillator of the respective plane. These features were determined by the entropy of the signals as well as based on preliminary tests. This brief investigation revealed no benefit in using Gaussian processes as the results, even when overfitting is controlled for, were not significantly better than the linear regressor. Thus, for our application, a linear regressor was trained and its output provided the final torque and position prediction.

Changes in the prosthetic's joint stiffness were implemented as a scaling factor for the overall stiffness pattern. The reasons for that are: (1) the stiffness signal from the 2DAPS algorithm is a control signal rather than actual active joint stiffness prediction; (2) modulating the overall stiffness by scaling provides more stability; and (3) discrete changes of stiffness are not necessary outside a complex balance task. The stiffness control signal has already been investigated, demonstrating that people are able to control it voluntarily during walking [233], and has been observed qualitatively to follow a similar pattern to ankle joint stiffness during gait. Thus, this signal was binned into three sections - low (stiffness signal < 0.3), medium (stiffness signal between 0.3 and 0.6), and high (stiffness signal > 0.6) stiffness. Thus, if the moderate or high threshold are passed, the overall joint stiffness is scaled by 1.5x or 2.5x respectively.

5.2.3 State and reflex control

The final part of the controller consists of a phase reflex rule, which allows a quick reaction to perturbations, a state controller to determine whether the user is in non-loading state (i.e. sitting/laying), standing, or attempting/performing locomotion, as well as a stance/swing length predictor.

The reflex rule for a phase reset, was inspired by the reflex occurring in mammals (including humans), where, depending on the phase that a perturbation (i.e. stumbling) occurs, either flexors or extensors are immediately recruited. For example, if a person stumbles over an obstacle during early swing, they will reflexively elevate and dorsiflex their foot, while if it happens during late swing, they will lower and plantarflex the foot. Similarly, for the foot that is in stance, the phase is elongated if the stumbling happened in early swing and cut short if it happened in late swing. This rule was identically applied for the prosthetic controller by detecting a perturbation (spike in foot contact force) during swing, and, depending on what phase of the swing it occurs, either maximally dorsiflexes the foot (early swing) or significantly plantarflexes the foot (late swing) leading to a phase reset. If the prosthetic foot was in stance and there was a disturbance in the forward acceleration (provided by the IMU), the stance phase was elongated.

The state of the prosthesis (unloaded/lightly loaded, transition to standing and standing, and transition to locomotion and locomotion) was determined by a classifier. Using features extracted from the EMG and IMU signals, sit-to-stand and stand-to-walk transitions were classified. The features used for the classification were mean absolute value (MAV), waveform length (WL), slope sign change (SSC), and zero crossing (ZC) extracted from the HDEMG, as well as MAV, minimum value, maximum value, standard deviation, and last value extracted from the IMU. These features were selected out of a wider range of features due to their impact on classification - adding any additional features did not result in significant classification improvements, while removing one of these did. The feature extraction sliding window was 200ms with an increment of 25ms, and the classifier used was a support vector machine using a cubic kernel. On classification, if a foot is unloaded or lightly loaded, position control was implemented

via the 2DAPS algorithm [233]. If a following transition to standing is detected, the foot's stiffness is increased to maximum and gradual plantarflexion torque is provided proportional to the foot's predicted position. If a consequent transition to walking is detected, the overall prosthetic algorithm for locomotion described here is used (with the oscillators and the reflex rule). However, for the standing period where no transition is detected, only the stiffness is kept at maximum and no torque is provided.

The gait phase length was also predicted in order to enable the switch between swing and stance position and torque control respectively. This was done by a very simple linear equation in the shape of $L = a \cdot x$, where "a" is a constant ($a=0.65$ for stance and $a=0.35$ for swing) and "x" is the length of the previous phase. Thus, if the previous phase was stance and the length was 700ms, then the length prediction for swing would be $0.35 \cdot 700$, which is 245ms. This simple approach was taken not because other approaches were not considered, but rather because it provided the most consistent behaviour while being the simplest. The other investigated approaches included extracting standard features from the IMU (mean, variance, standard deviation, minimum and maximum value) and EMG (mean absolute value, waveform length, and zero crossing) data, as well as doing the feature extraction using a data-driven approach via a convolutional neural network. These feature extraction approaches coupled with different classifiers (linear regression, support vector machine, and neural network) did not provide any benefit in regards to the simple linear approach. Furthermore, the observed errors in gait phase length using the simple linear approach were below 20ms, which were satisfactory for the overall gait speed modulation (see more in the results section).

5.2.4 Evaluation

The evaluation of the controller is performed offline, using the data that was recorded in Chapter 4, including the estimates provided by the 2DAPS algorithm provided in real-time during the recordings. The controller itself hasn't been tested in real-time with a prosthesis being controlled by it, apart from the prosthesis integration work reported in Chapter 3, which demonstrate its embedding and work in real-time with a prosthesis, which was outputting and

recording values without walking/using the prosthesis.

Metrics

For evaluation of the controller, I have computed the root-mean-square error (RMSE) and cross-correlation (XCOR) between the true values and the predictions across a variety of conditions, all the data for which is provided by the dataset described in Chapter 4. To investigate the difference between a general controller and a subject-specific one, these metrics were computed either on within-subject basis or across-subject basis. When computed on within-subject basis, the training and test data were based on repetitions - two repetitions for training and one repetition for testing for each locomotion condition. When computed on across subject basis, the training and test data were separated by subject, running a leave-one-out 10-fold cross-validation with nine subjects used for training and one for testing across all conditions. Furthermore, I have quantified the differences between locomotion conditions (level-ground, ramps, and stairs) for both conditions by computing not only the overall RMSE and XCOR but also the ones within the locomotion conditions. The average virtual stiffness signal was also computed across locomotion conditions.

The stance/swing length classification were also computed on an individual basis as well as using a leave-one-out 10-fold cross-validation with nine subjects used for training and one for testing. The non-loading/standing/locomotion state classification was also assessed on individual basis and a standard 10-fold cross-validation, with a classification loss function in the form of:

$$L = \sum_{j=1}^n \omega_j e_j \quad (5.6)$$

where ω_j is the weight for observation j (the weights are renormalized to sum to 1), $e_j = 1$ if the predicted class of observation j differs from its true class, and 0 otherwise, and n is the number of observations. This loss was used so that the classification error is the proportion of observations misclassified by the classifier, as the data set is unbalanced (more walking observations than sitting, standing, and transitions).

Statistics

All the statistical analyses were performed using either a t-test (for the overall comparisons represented in the box-plots) or an Aligned Rank Transform (ART) ANOVA (for the within-task comparison represented in the line-plots). The assumptions for these tests were checked beforehand by using a Shapiro-Wilk test to check if the residuals are normally distributed and a Bartlett's test to check the Homogeneity of variances of the data. The ART ANOVA analyses were performed in R 4.2.1 [278] using the ARTool library [325] and the t-test analyses were performed in Python 3.7 [326] using the scipy.stats library [327]. The statistical significance code used for the rest of the chapter is as follows: *** for $p < 0.001$, ** for $0.001 \leq p < 0.01$, * for $0.01 \leq p < 0.05$, and '.' for $0.05 \leq p < 0.06$.

The comparison of means for the overall torque and position metrics performance using a subject-specific and across-subject controller training was performed using a student's t-test. The normality and Homogeneity of variances assumptions were satisfied for all analyses apart from the frontal plane XCOR position analysis, where a Mann-Whitney U rank test was performed. The state classification comparisons were also executed using this t-test procedure

The within-task metrics comparison of the differently trained controllers for torque and position was performed using an ART ANOVA. This was due to the non-normal distribution of the residuals, which required a further aligned rank transform [325] before executing the ANOVA procedures to correct for this non-normality. The gait phase classification comparison between the training types was also executed in this way.

5.3 Results

5.3.1 Controller Performance

The overall results presented here are achieved with the controller method described above. Results with the non-linear (Gaussian process regression) approach were not included since they

were not significantly different from the linear controller ($p > 0.05$). In this section, I wanted to investigate not only how the controller performs, but also its ability to generalize across subjects. This is very important since, in the ideal case, the controller is sold as a package along with the prosthesis and there shouldn't be any need for additional data collection, which can be expensive and time-consuming. The results presented in Figure 5.2 and Figure 5.3 illustrate the difference in torque and position performance respectively between the individually trained

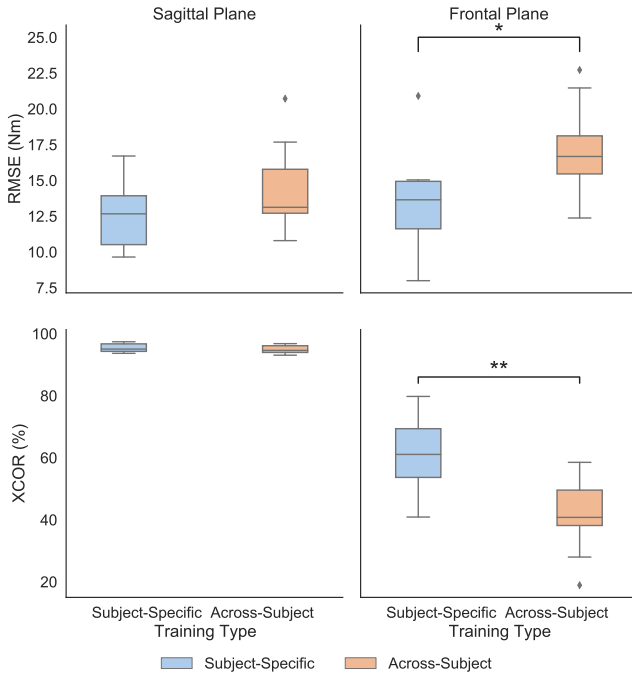


Figure 5.2: Comparison of torque results for the subject-wise and across-subject controller training during stance phase. Error bars represent 95% confidence interval (CI) derived from results of different subjects (subject-specific training) and during cross-validation (across-subject training).

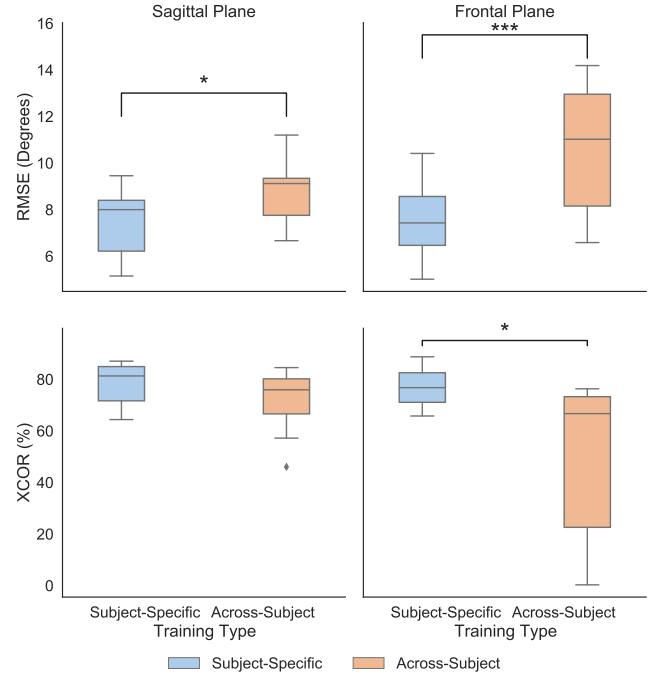


Figure 5.3: Comparison of position results for the subject-wise and across-subject controller training during swing phase. Error bars represent 95% CI derived from results of different subjects (subject-specific training) and during cross-validation (across-subject training).

controller and the general one. The predictions of the general controller in the sagittal plane torque show very high cross-correlation (mean XCOR = 94.91%) and a moderate amount of error (14.24 Nm RMSE). Sagittal plane position results were lower (average XCOR of 71.72% and an RMSE of 8.82°) but still acceptable. The frontal plane torque, however, shows lower cross-correlation and higher errors (average XCOR = 41.2% and average RMSE = 17.2Nm) and will need improvements. Similarly, frontal plane position also shows much larger variations (average XCOR = 50.3% and average RMSE = 10.6° and might need improvements before it

is implemented within the prosthesis. The comparison between training type (individual or across-subjects) show no statistically significant difference in the sagittal plane for both torque and position ($p > 0.05$) apart from a small difference in the sagittal plane position RMSE (t-statistic = -2.11, $p = 0.049$). However, the subject-specific controller was found to perform better in the frontal plane torque (t-statistic = -2.53 and $p = 0.02$ for RMSE, and t-statistic = -3.41 and $p = 0.003$ for XCOR) and position (t-statistic = -3 and $p = 0.0007$ for RMSE, and t-statistic = 19 and $p = 0.01$ for XCOR). This is expected as there is a much higher variation in frontal plane kinematics and dynamics of the foot between subjects. To further quantify the error contribution of each locomotion mode (level-ground, stairs, and ramps) for both controllers, the within-mode metrics were computed as well.

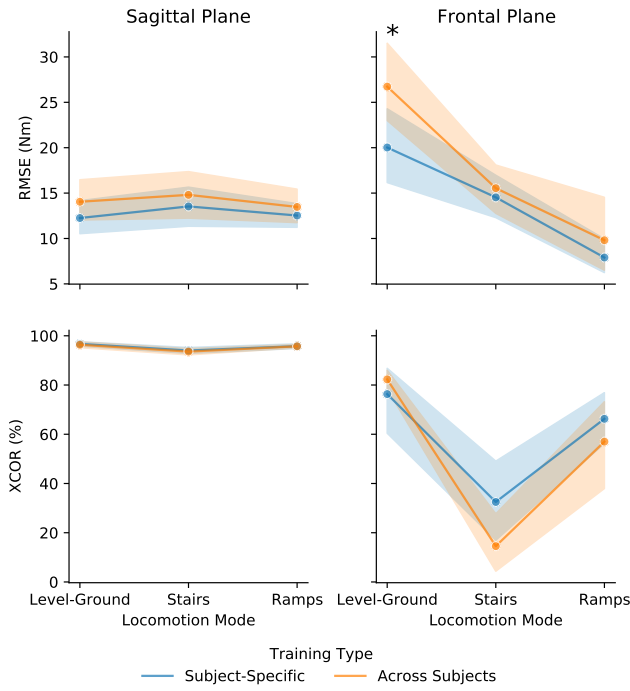


Figure 5.4: Within-task metrics comparison of torque results for the subject-wise and across-subject controller training during stance. Shaded area represents 95% CI derived from results of different subjects (subject-specific training) and during cross-validation (across-subject training). Statistical significance between training type indicated above the respective locomotion mode.

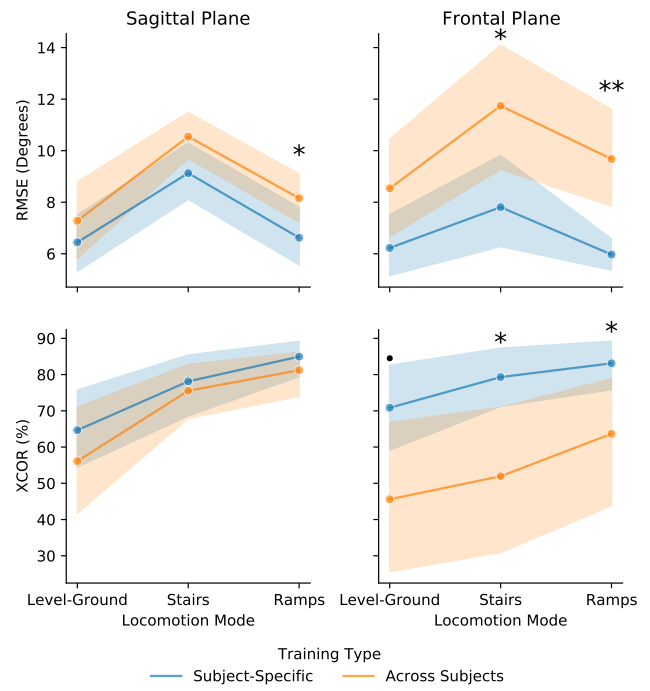


Figure 5.5: Within-task metrics comparison of position results for the subject-wise and across-subject controller training during swing. Shaded area represents 95% CI for different subjects (subject-specific training) and cross-validation runs (across-subject training). Statistical significance between training type indicated above the respective locomotion mode.

Figures 5.4 and 5.5 similarly show no within-task differences between the controller training

in the sagittal plane, apart from position RMSE results (t -ratio = 2.032, $p=0.047$). Frontal plane position result differences between the two training types were more pronounced: t -ratio = 2.549 and $p=0.01$ for Stairs RMSE; t -ratio = 2.99 and $p=0.004$ for Ramps RMSE; t -ratio = -1.989 and $p=0.052$ for Level-Ground XCOR; t -ratio = -2.4 and $p=0.02$ for Stairs XCOR; t -ratio = -2.089 and $p=0.004$ for Ramps XCOR. There was also a small difference between training type in the frontal plane torque RMSE for the Level-ground walking task (t -ratio = 2.192, $p=0.033$). Interestingly, we can notice similar trends for both training types. These include higher position RMSE during stair ambulation and linearly increasing XCOR between locomotion modes, as well as a lower frontal plane torque XCOR during stair ambulation and a linearly decreasing trend in the frontal plane RMSE between locomotion modes. Since the algorithm's virtual stiffness signal has no validation method, the average stiffness signal was plotted as a sensibility indicator. For example, one would expect the signal to be lower during

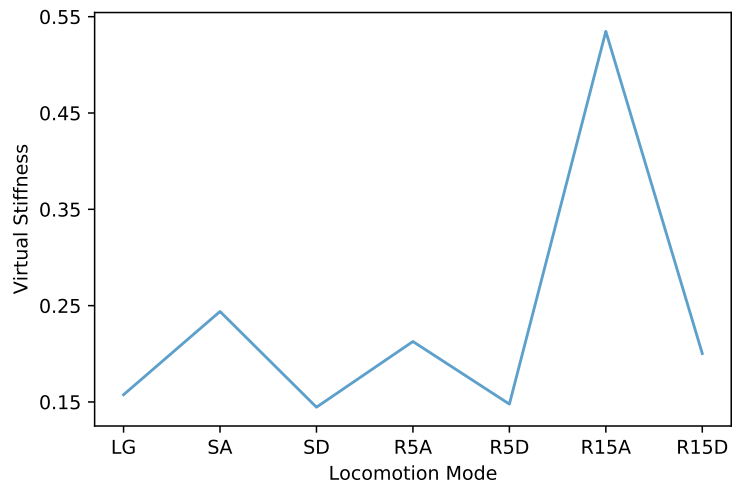


Figure 5.6: Virtual stiffness signal across locomotion modes.

level ground than during stairs and

ramps ascends. The results shown in Figure 5.6 indicate that, on the average, indeed there is an increase in the stiffness signal during the stairs and ramps ascend tasks compared to level ground and descend tasks. Furthermore, the 15° ramp ascend shows the greatest increase, which is reasonable since the incline is quite steep and people need larger stability during the task. This increase was even evident in the 15° ramp descend, albeit to a smaller degree due to it being a descend task.

5.3.2 State Classification

The classification errors for swing/stance state and the classification loss and confusion matrix for the non-loading/standing/locomotion state are presented in Figures 5.7, 5.8, and 5.9 respectively. The swing/stance length estimation results demonstrate that subject-specific training performs significantly better ($p < 0.0001$) than the general training with average stance length RMSE of 102ms (231ms for the general) and swing length RMSE of 31ms (94ms for the general).

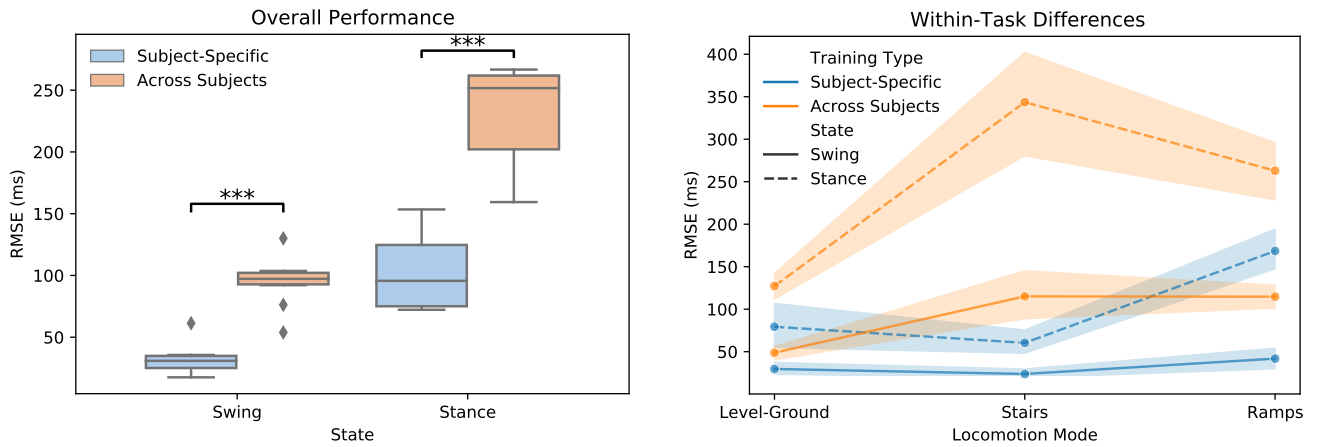


Figure 5.7: Gait phase classification results, showing overall performance (left) and within-task performance (right). Shaded area and error bars represent 95% CI derived from results of different subjects (subject-specific training) and cross-validation runs (across-subject training). The significance level for the "Within-Task Differences" plot is not indicated as all the differences in training types are statistically significant ($p < 0.0001$).

Interestingly, the subject-specific trained classifier errors during ramp were much larger during stance than during the rest of the locomotion tasks (Figure 5.7). For the across-subject trained one the errors were much larger during the ramp task but even more so during the stairs ambulation. Another easily observed trend is that the subject-specific trained controller performed

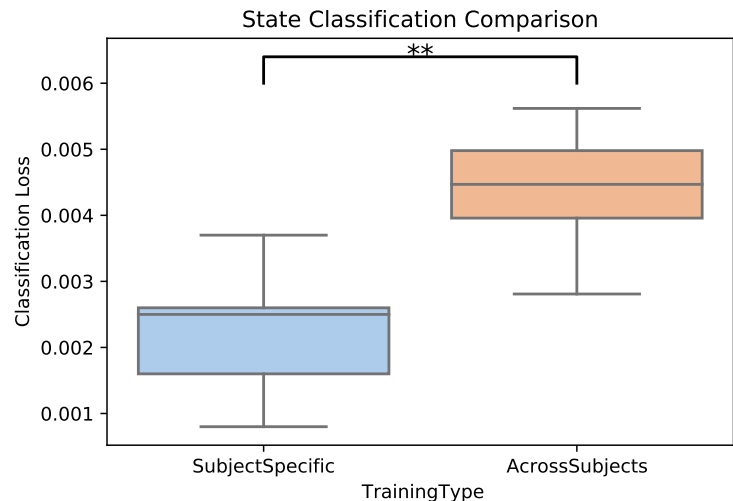


Figure 5.8: State classification loss comparison (using equation 5.6). The error bars represent 95% CI derived from results of different subjects (subject-specific training) and cross-validation runs (across-subject training).

significantly better ($p < 0.001$) compared to the general controller, indicating a need to improve generalizability. On the contrary, the non-loading/standing/locomotion state classification loss, although statistically significant ($p = 0.0018$), was quite similar between the individually trained classifier and the across-subjects one, with average loss of 0.0023 and 0.0043 (Figure 5.8). Furthermore, if we look at the confusion plot (Figure 5.9), we can notice that the lower loss of the individually trained classifier might come at a cost of higher misclassification of a certain state - sit-to-stand transition in this case.

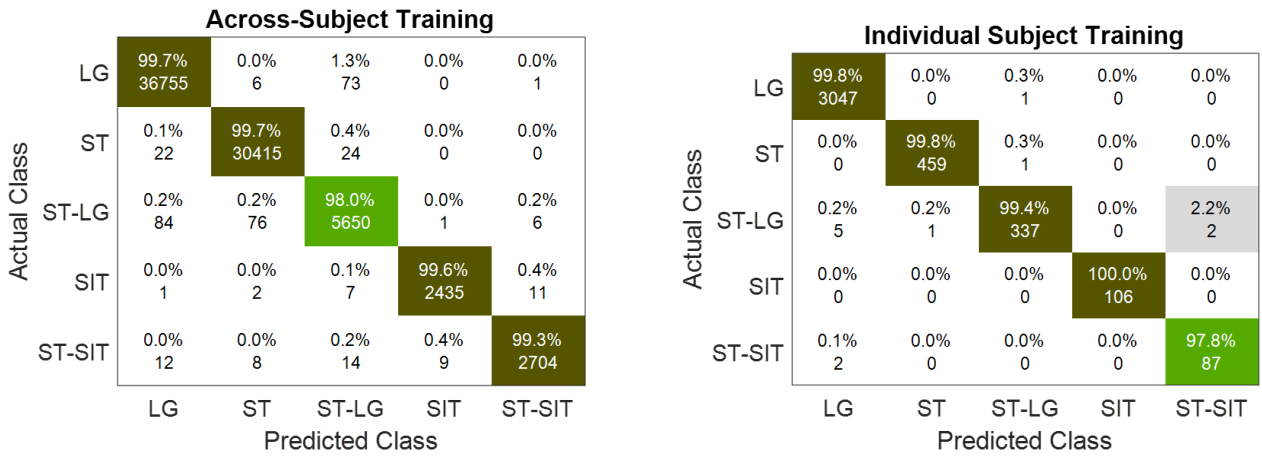


Figure 5.9: State classification confusion plot comparison with labels signifying: LG (level-ground), ST(standing), SIT (sitting), ST-LG (transition between level-ground and standing), and ST-SIT (transition between sitting and standing).

5.4 Discussion

The results above demonstrate the capability of the embedded prosthetic controller to generate reliable predictions for 2 DoFs torque and position based only on below-knee sensor data. The overall generalizability achieved here is very important as it is a needed feature if this is to be adapted by the industry. The reason for this is the high cost that an individual-specific controller entails in terms of generating such data - motion capture and sensor equipment, professionals' time (prosthetists, rehabilitators, engineers, etc.), and user's time. Considering this, it is critical for the controller developed here to have a reliable general swing/stance length prediction. This, evident from the results above, needs an improvement as only the subject-specific classification scores can be currently used for such an approach. However, the

loading state classification provides a very reliable performance and can be implemented within a prosthetic controller.

In general, the torque and positions predictions in the sagittal plane were acceptable and comparable to other recently developed approaches for ankle torque and position estimation [328, 329, 330]. A few significant advantages that the work presented here has, is the ability of the controller to generalize between users and provide additional signals without the need for computationally expensive models and/or difficult to obtain data. This is very important for prosthetic implementation since performing heavy computations in real-time are difficult tasks. Also, controllers relying on accurate lower-limb joint angles for ankle position and torque can struggle without motion capture generated features. Moreover, this developed controller additionally provides frontal torque and position as well as a virtual stiffness signal. This is important during locomotion, as we know from previous studies that stiffness modulation is imperative for stabilizing locomotion during unstable ground conditions (slippery or uneven) [30, 31, 32]. The frontal DoF has also been shown to be important for prosthesis use during sidestepping [289], activities of daily living [262], and play an important role in whole-body angular momentum [253]. Another important distinction that this controller has is its continuous approach, without a need for classifying different locomotion modes, with performance that is comparable across ambulation conditions and walking speeds. The controller still relies on two classifiers for the loading condition and the stance/swing length. While the loading condition has exceptional performance and is likely to be utilized without any problems, the stance/swing length classifier will need improvements to enable a good across-subject performance.

The stiffness signal information throughout locomotion was able to provide sensible input as well, demonstrating expected differences across ambulation conditions. This is very positive trend, but would need to be investigated further when implemented for a real-time control. On the real-time prosthetic implementation, this controller has been shown to be very light and easily integratable within the prosthesis control loop. This shows a great promise for the future study that will involve a real-time locomotion with a transtibial prosthesis participant. This is needed to assess how the controller errors translate during locomotion.

5.5 Conclusion

The final developments and studies presented in this chapter demonstrate the structure and function of the complete prosthetic controller, including performance results and implementation. The controller demonstrated a good performance for sagittal plane torque and position prediction while additionally providing sensible frontal plane predictions and a virtual stiffness signal. This controller's integration with a prosthetic hardware was also done (see Chapter 3), showing the computational time and data transfer to be sufficient and way within the limits of such hardware. However, work still needs to be done to improve predictions of stance/swing length and frontal plane ankle torque and angle in order to minimize the risk for users. Finally, this work will need to be tested during a study with a transtibial prosthetic user(s) to assess the implications, which such controllers can have on a prosthetic user's gait.

Chapter 6

Conclusion

6.1 Summary

The work presented in this thesis mainly sought to develop, implement, and test a complete prosthetic controller, with further exploring the impact of direct user input for prosthesis control and the implications of such a 2 DoFs approach for long-term use.

The control algorithm development approach was initiated by exploring and selecting a method for extracting user input for the phantom foot's position and stiffness signal in the sagittal and frontal plane. This method was tested during two experiments involving eight participants without amputations and two(voluntary control)/one(gait study) participants with a unilateral transtibial amputation. These experiments revealed a high control accuracy and no difference in control ability between participants with and without an amputation. Furthermore, it demonstrated no difference in performance caused by adding 2 DoFs stiffness control or by reducing significantly the number of channels (from 192 to 24 electrodes). That provided confidence in this method for user prosthetic input.

The development of the control algorithm was pushed further to completion by devising an approach for providing safe and stable gait oscillations. This approach consisted of non-linear oscillators that were working in tandem to learn and reproduce an average walking pattern

for the foot's position and torque during swing and stance respectively. This was further supplemented by providing modulation to the oscillators based on the previously developed user input and the prosthetic foot contact information. In order to train and preliminary test the performance of such controller, a number of technical solutions needed to be developed and provided to enable the collection of a comprehensive human locomotion dataset.

The technical solutions included: the design and implementation of a body-wearable HDEMG system (including electrodes, amplifier, and software); a custom one-size-fits-all garment to house the wearable system; mobile application for display and control; and the implementation of the full system (including a novel IMU sensor) within a microcontroller. All of these elements were incrementally developed and tested, ensuring the stability and robustness of the system for a real-time use. Due to the developments being implemented largely during the pandemic, it also gave a realistic perspective for the home use of this system and the necessities it required.

With the completion of the wearable system, a comprehensive locomotion data collection was initiated with 10 able-bodied people (five male and five female). This study included the collection of motion capture, force plates, IMU, and HDEMG data throughout the variety of conditions consisting of level-ground walking and stair and ramps (5% and 15% incline) ambulation at different walking speeds (slow, self-selected, and fast) as well as stand-to-walk, sit-to-stand-to-walk, and sidestepping (to the left and right). Using this data, the complete control algorithm was trained and assessed offline.

The final challenge left was implementing and testing the controller with a prosthetic device. For this, a three-month research visit at Prof Hugh Herr's group at the MIT Media Lab was arranged. Throughout this visit, the prosthetic controller was fully implemented within the prosthetic device's embedded controller. This implementation was tested in real-time by walking and recording the controller and prosthetic output to make sure that they were matching and the commands were within the update frequency of the prosthesis. Unfortunately, the final testing involving users with a unilateral transtibial amputation using the device and controller was not performed. This was due to unavailability of participants with unilateral transtibial amputations throughout the research visit.

6.2 Main Achievements

The main achievements of this thesis that extend the state of the art in the field are: (1) the 2DAPS algorithm providing a novel neural signal for stiffness control from high-density electromyography (HDEMG) on top of 2 DoFs kinematic estimates; (2) novel biologically inspired hybrid control strategy including a rhythmic automatic component modulated by a neural component obtained at the muscle level; (3) novel universal and wearable HDEMG electrode design and interface for in-socket recordings at the lower limb; (4) publicly available sensor-rich data set for an extensive variety of locomotion activities. Achievements (1) and (2) have been tested and validated, with the results available in their respective chapters (2 and 5) demonstrating their viability. Achievements (3) and (4) will be made publicly available, thus everyone will have access to these resources, which are meant to serve as a publicly-available tools for physiological recordings and benchmark for comparisons.

6.3 Limitations

The main limitation of this thesis is the lack of evaluation during locomotion with prosthesis users. This was unfortunately due to unforeseen circumstances with both COVID-19 and participant recruitment during the stay at MIT. This planned study was supposed to focus on assessing how user input and additional DoF and stiffness signal affect the gait asymmetry and stability during different locomotion conditions as well as test the general robustness through a day-long assessment. These issues are critical, because it is hard to assess what does an RMSE of 10Nm translate to for the overall gait, since the overall effect is provided by interactions between the user and environment. Similarly, the controller's performance needs to be assessed throughout the day to evaluate its ability to perform when the person is tired or accidentally hits an obstacle, etc. I am hoping that I will be able to execute this study in the near-future, providing answers to these important questions. It needs to be mentioned here that this work has also spanned further research in the avenue of locomotion recognition.

Another limitation that does not come across from the text in this thesis is the short amount of

time for the final control structure exploration. Initially, this work was supposed to be supported by a large prosthetic company, which would have provided a prosthetic device and a wearable prosthetic liner with embedded EMG electrodes. Thus, the focus of this work would have been solely on the control. However, due to unforeseen circumstances, this arrangement fell through and the engineering challenges for a wearable HDEMG system and prosthetic integration had to be done by myself. This in turn shortened the final time for control structure exploration towards the end of the PhD. Although it is hard to quantify the impact on this and how much that would have changed the final structure and results, it is still a notable mention as to the reason why further improvements on this strategy have not been explored yet.

6.4 Future Directions

6.4.1 Pending/Open Research Work

There are four specific avenues that the direction of this work is currently focused: (1) real-time evaluation of the controller with prosthetic users; (2) exploring the controller's application in ankle exoskeleton control; (3) further utilizing the 2DAPS algorithm's feedback for rehabilitation targets and stimulation timing; (4) employing the data collected in Chapter 4 for locomotion mode recognition.

Continuing from where this current work stopped, the first explored avenue is planned to be an evaluation of the controller's safety during prosthetic gait. Moreover, such work can provide answers about improvements in lower back loading, asymmetry, and metabolic work during walking on uneven terrains, turning, and balancing tasks. For this, there is already an available active 1 DoF ankle prosthetic device, ordered and assembled by myself, which will be used to provide full safety evaluation. Following this, the study described briefly in the Limitations section above will be executed to assess the utility of including stiffness control and user input in general. This is extremely important as it can provide an initial answer to the questions that these developments aimed towards - is user input necessary for reduction of excessive

asymmetrical loading, how effective is the described prosthetic stiffness control for locomotion stability provision, and how robust is a HDEMG wearable for daily use.

In conjunction with this first avenue, implementation of the 2 DoFs controller will be explored in an exoskeleton application. A 2 DoFs exoskeleton device was developed by a colleague of mine and we will work together to simultaneously assess the exoskeleton hardware and the controller's capabilities. Of course, necessary adjustments will have to be made and there is a large difference between assistive and prosthetic gait. However, this can provide initial insights of the direction that the answers are going and prepare for subsequent work with a 2 DoFs prosthetic device once it becomes available.

Another avenue that I am personally pursuing is for a physiological and rehabilitation supportive tool, which informs clinicians about phantom movements and capabilities during their work with people with transtibial amputations. There was expressed interest from rehabilitation professionals about this as well as using the information for a feedback mechanism during rehabilitation sessions. This can be used to assess motor control and ability of a person with an amputation and track their progress throughout the rehabilitation process. Further work exploring the general utility of the algorithm for phantom foot feedback is part of a project of another colleague of mine. His work on electrical stimulation for sensory input restoration prompted a further application for the 2DAPS algorithm. This particular research will aim to investigate using the phantom foot's position and stiffness predictions for provision of sensory stimulation feedback.

Lastly, during the last year of the project I have proposed and supervised, along with my supervisor (prof. Anthony M. J. Bull), a masters project that used the data obtained in Chapter 4 to classify locomotion modes. This work has achieved results ($<99.6\%$ overall classification accuracy) that are a significant improvement over the current research, realizing that by utilizing standard classification techniques. That suggests a great utility of HDEMG signals for such tasks, since this was the only major difference when compared to other current research. This work will be submitted for publication and further investigated applying novel classification algorithms.

6.4.2 Broader Research Applications

In general, the daily wearability of HDEMG and quality changes throughout a variety of activities of daily living is important to be quantified. Because, if this setup is successful in achieving a consistent behavior, as observed during the prolonged lab testings, then it will open another avenue of explorations involving HDEMG. Up until now, HDEMG applications like this and many others are predicated on the assumption that such an approach is reliable for daily use, which has so far been investigated only in lab conditions. The positive thing is that we finally have a wearable platform, showcased in this work, which enables easy testing outside the lab and in home conditions that can provide an answer to the HDEMG robustness and usability question. Thus, general questions on motor control, activation patterns and adaptation throughout rehabilitation, training, or a developmental period can be explored by scaling the current setup to cover the whole lower limb musculature. Since the setup is modular and does not rely on having tethered equipment, such studies can be done in an outside environment or a rehabilitation/clinical setting without the need for additional equipment.

Furthermore, since the data generated in Chapter 4 will be made publicly available, it can be further utilize for answering some of the questions on detailed muscle activations and patterns across activities and speeds as well as serve as a benchmark and a source of data for classifiers of different types (locomotion mode, gait phase, loading mode). So far, we have utilized this only in the exploration for the importance of HDEMG data for locomotion mode recognition, but this can be explored and pushed much further applying different algorithms and strategies to bring the accuracy of such approaches as close to 100% as possible. The data can also be used to study synergistic activations across the different task, or collect further data with the described setup of a certain type of population of interest and compare across different cohorts. Another set of activities can be acquired outside the lab using markerless tracking (via phone cameras) including running, jumping, acrobatics, ballet, and be utilized to study completely different, non-gait, activities for investigating strategies of motor control.

Another avenue to explore is to utilize the availability of the whole prosthetic control platform to innovate in certain sections of the control level without having to devise a complete control

platform from scratch. Since 2 DoFs of active control has been poorly explored, this platform offers a great mechanism to explore different strategies. For example, one can explore how to combine the neural and the mechanical inputs in different ways, does a strategy with a varying neural involvement into the rhythmic patterns dependant on activity is better suited, is a rhythmic component or classifiers at the high level needed at all or a better performance can be achieved in a completely different way, etc. Furthermore, since it is a complete control package, including the human in the control loop, providing 2 DoFs control, integrating it with high-level classifiers for gait phase and loading condition, it presents a platform for testing different hypotheses. One avenue could be to investigate different strategies at any of these levels (high, mid, and low) without the need of creating a complete controller from scratch. Another avenue could be to investigate perturbation strategies and how errors across the gait cycle affect (and to what extend) the user, if they are allowed to compensate for such perturbations. The control strategy itself can also be easily expanded to a transfemoral prosthetic controller or a bilateral controller by just replicating the same procedure for the needed level. The mobile application can also be used to switch between different controllers in real-time and investigating the effects of them outside the lab.

The prosthetic controller, the wearable setup, the data set, and the 2DAPS algorithm can be used in a variety of ways, not only pertaining to prosthetic control but also expanding into other areas. As previously mentioned, the control paradigm can be used in exoskeletons, where you need the human-in-the-loop control. An important aspect for the human-machine interaction with such systems is the stiffness/compliance of the joints and the force grip that is applied by them. Thus, the virtual stiffness signal approach, devised by this work can be used for the improvement of such human-robot interactions. Furthermore, the wearable system can also be used and expanded upon a general active-wear clothing, where it provides information about muscle fatigue, asymmetries during training/daily activities, feedback/adherence for on-line trainers and coaches, recovery rates, along with the standard heart-rate monitoring and perspiration.

Undoubtedly, this dissertation opens multiple avenues and questions to be answered, but this is personally exciting for me and motivating to pursue these scientific unknowns.

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