Coordination of Lower Limb Movement Utilizing the Agonist-Antagonist Myoneural Interface

by

Tony Shu
B.Sc., Georgia Institute of Technology (2016)

Submitted to the Program in Media Arts and Sciences
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Author .................................................................
Program in Media Arts and Sciences
August 9, 2019

Certified by ............................................................
Hugh Herr, Ph.D.
Professor of Media Arts and Sciences
Thesis Supervisor

Accepted by ............................................................
Tod Machover, Ph.D.
Academic Head, Program in Media Arts and Sciences
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Abstract

The agonist-antagonist myoneural interface is a novel surgical construct that shows promise as a method of providing persons with amputation proprioceptive sensation of movement and force.

This thesis aims to quantify the volitional coordination capabilities of the agonist-antagonist myoneural interface for applications related to control of active prostheses. In the first section, bilateral rhythmic coordination of ankle and subtalar joint movements is investigated in a control group of physically intact human subjects to characterize stereotypical kinematics of volitional lower limb movement. Subsequently, neuromusculoskeletal modeling techniques are developed to directly map estimated neural excitations from agonist-antagonist myoneural interface musculature to intended subtalar inversion and eversion kinematics.

In a case study, the developed neuromusculoskeletal modeling techniques are applied to optimize a dynamic subtalar model for use by a unilateral subject with amputation possessing the agonist-antagonist myoneural interface. The subject’s subsequent performance in bilateral rhythmic coordination utilizing the model and her own intact subtalar demonstrates the capacity of the agonist-antagonist myoneural interface to coordinate with intact anatomy in a biomimetic manner.

Thesis Supervisor: Hugh Herr, Ph.D.
Title: Professor of Media Arts and Sciences
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Tony Shu

The following people served as readers for this thesis:

Thesis Reader .................................................................
Edward Boyden, Ph.D.
Y. Eva Tan Professor in Neurotechnology
McGovern Institute for Brain Research

Thesis Reader .................................................................
Neville Hogan, Ph.D.
Sun Jae Professor of Mechanical Engineering
Department of Mechanical Engineering
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Chapter 1

Background

This chapter provides a relevant overview of human motor function, biomechanics, and amputation to explain how residual musculature can be used to volitionally control an active prosthesis. Much of this thesis is based on extant literature regarding upper limb control, and additional background is given on the methodologies adapted within for characterizing volitional control of physically intact and amputated lower limbs.
1.1 Motivation

Passive lower limb prostheses are fundamentally incapable of replicating the dynamics of human locomotion. The advent of microelectronics and high power density electric motors has allowed researchers to develop active prostheses that seek to recover this functionality for persons with lower limb amputations [1]. However, while locomotion is essential, the purpose of a prosthesis should not be limited to an explicit function of this single ability.

Ramachandran and Rogers-Ramachandran [2] famously demonstrated the power of embodiment, or limb ownership, through what is now known as mirror therapy. As persons with unilateral upper limb amputation had their intact limb visually superimposed over the spatial location of their phantom limb, perceived kinesthetic sensations were elicited from the phantom related to manipulation of the intact limb. Similarly, the capacity to express volitional lower limb behaviors such as foot tapping, leg crossing, and even simple fidgeting through an active prosthesis may grant the owner with an even greater sense of embodiment, yet these remain unrealized on devices that have already satisfied the power and mechanical bandwidth requirements.

The agonist-antagonist myoneural interface is a novel surgical construct for persons with amputation that physically links two residual muscles, causing contraction of one to pull the other. This mechanical linkage should establish a way to perceive the movement and force levels of both muscles via preexisting embedded mechanoreceptors. What remains is to create a mapping for this construct so that control of an external device matches exactly what the user perceives internally. Accuracy of both internal feedback and external actuation may not only restore embodiment to persons with amputation, but may also produce new paradigms for control of non-anthropomorphic machinery by physically intact humans.
1.2 Neuromusculoskeletal Modeling

Before characterizing a system, it is worthwhile to determine the scope and scale of interest. This section details how neural excitations cause muscle contraction to produce forces and motion in the lower leg.

1.2.1 Anatomy of the Lower Leg

The lower leg, as it is referred to in this thesis, is skeletally comprised of the tibia, fibula, and all bones relatively distal. It includes all muscles and immediate structures that affect the ankle and joints of the foot. Figure 1-1 shows the general region of interest. Defining coordinates intrinsic to the body is also helpful when describing human anatomy and motion. Relative anatomical orientations and planes are shown in Figure 1-2.

The ankle is truly a single joint known scientifically as the talocrural joint. The talocrural joint forms the axis of rotation for ankle dorsiflexion and plantarflexion (DP). It is plantarflexion that propels the body forward in the sagittal plane during level-ground walking. Tiptoeing and jumping also involve extensive rotation of this joint. The subtalar joint, located closely to the talocrural, forms the axis of rotation for foot inversion and eversion (IE). Actuation in these directions promotes stability in the coronal plane during quiet standing and locomotion.

The muscles which actuate the talocrural and subtalar are numerous, but only 12 are responsible for the majority of motion [1]. These muscles are extrinsic; they insert into the foot but originate proximally to the knee. The major plantarflexors include the medial gastrocnemius, lateral gastrocnemius, and soleus. The primary dorsiflexor is the tibialis anterior. The major inverter is the tibialis posterior, though the tibialis anterior and soleus also contribute to this motion, and the major everter is the peroneus longus (PL). It is necessary to state that the muscles of the lower leg do not contribute purely to a single degree of freedom. The sophisticated skeletal structure and varying muscle wrapping surfaces of the ankle-foot remain a challenge to fully model, but making a few modeling assumptions generally allows researchers
1.2.2 Biomechanics of Movement

Upon initial consideration, movement is simple. Humans do it “without thinking” all the time, every day. However, even a passing interest in movement raises difficult questions. Why do babies require around a full year before learning how to walk while hoofed animals can do so almost immediately after birth [5]? How do jugglers keep several balls in the air without even opening their eyes? Explanations vary widely in scope and detail.

Organismal biomechanics concerns the animal as a whole and focuses on how forces
can be generated by skeletal muscles to produce motion (or lack thereof). Muscles are actuators which only contract. Skeletal muscles are always found in series with tendons that anchor to bone. By contracting, muscles can generate moments of force about a joint at some distance away from the axis of rotation, producing a net torque trajectory according to

\[
\tau_{\text{net}}(\theta, t) = \sum_{i=1}^{n} r_i(\theta) F_i(\theta, t) \tag{1.1}
\]

where \( n \) is the total number of muscles acting about a joint, \( r_i(\theta) \) is the effective moment arm length of muscle \( i \) dependent on joint angle, and \( F_i(\theta, t) \) is the instantaneous force of muscle \( i \) at time \( t \). The torques generated by all muscles and other contributors such as passive ligaments, sliding fascia, joint capsules, and external forces like gravity and environmental contact can be summed to determine the dynamics of a moving biological system through the Newton-Euler equations of motion.

As a result of skeletal muscles being strictly contractile actuators, they are always paired with at least one other muscle so that contraction of one can be counteracted by contraction of the other to produce full range of motion at the joint. The biceps
and triceps muscles of the upper arm are classical examples of this agonist-antagonist configuration. While seeming like a limitation at first, the implications are actually quite useful for animal movement. By varying the muscle activation levels of the agonist and antagonist, equivalent to scaling their force production, the net torque generated about a joint can be independently modulated from its mechanical stiffness, or torque generated per unit displacement \[6\]. Stiffness is a result of simultaneous agonist and antagonist coactivation, also known as cocontraction, and may be intuitively understood by holding your hand out and squeezing all of your muscles without actually moving your arm. Modulation of joint stiffness is vital for successful completion of all tasks including walking without tripping, using a screwdriver without the tip slipping, and typing up thesis sections on a keyboard.

1.2.3 Proprioception

Muscles and tendons are embedded with a diverse set of biological mechanoreceptors which inform us of our body’s internal dynamics in addition to the dynamics of our limbs in space. This sensory awareness, called proprioception, is a critical contributor to our ability to generate robust motion in unknown environments and in the presence of disturbances, even without visual feedback. Proprioceptive signals are afferent, meaning they conduct information toward the central nervous system. This is opposite of efferent signals which conduct information away from the central nervous system. Though a variety of mechanoreceptors exists, only the three most closely related to the muscles and tendons are discussed here.

Muscle spindles are organs embedded within intrafusal muscle fibers in parallel that provide the central nervous system with muscle length and velocity information. There are two types:

- Type Ia: responds to rate of change of muscle length and is somewhat sensitive to static muscle length
- Type II: responds to static muscle length only
Combined, these two signals are enough to calculate the position and velocity of a limb in free space.

![Figure 1-3: Type Ia muscle spindles spiraling around intrafusal muscle fibers](image)

Golgi tendon organs are separate mechanoreceptors that are embedded in the tendons at both the origin and insertion ends of a muscle. As they are in series with the muscle, they provide afferent information about the forces generated by the muscle.

Referring back to the agonist-antagonist configuration of muscles, it can now be understood how activation of the agonist produces rotation at the joint and corresponding stretch of the antagonist to provide a sensation of position and motion from both muscles. However, this is only true when impedances are sufficiently low to allow motion in the first place. When the limb is loaded against an obstacle like a wall, agonist activation produces no afferent feedback from the antagonist corresponding to motion. Instead, the increasing afferent signals from the agonist’s Golgi tendon organs and muscle spindles inform the central nervous system of mounting levels of tension and contraction.
Spinal Reflexes

Spinal reflexes rely heavily on afferent feedback from proprioceptive sensation. Briefly, spinal reflexes are involuntary excitatory or inhibitory modulations of alpha motor neuron activity that can either elicit or inhibit muscle activation. As the name implies, the interneuronal networks responsible for these reflexes are unique in that they are located solely in the spinal cord. Well-known reflexes include the stretch or myotactic reflex which prevents a muscle from overlengthening and damaging itself. When this occurs in the knee, it is known as the knee-jerk or patellar reflex and causes the subject to kick out. Spinal reflexes activate quickly due to the relatively short distances required for nerve action potentials to travel (compared to a round trip to and from the brain).

While spinal reflexes are important for dynamic tasks such as walking and running, they are assumed to be largely inactive during the experiments performed in this thesis. Instead, this work focuses on volitional control of movement which is informed by the brain’s motor cortices.

1.2.4 Hill-type Muscle-Tendon Units

To mathematically model muscles for the purposes of computational simulation, dynamic models based on the work of A.V. Hill are constructed to represent the known dynamic features of real muscles. These modeled muscle-tendon units (MTUs) are formulated by a transfer function modulated by both physiological parameter constants and muscle state variables to relate muscle activation, usually derived from electromyography in practice, to output force. The cumulative effect of all MTU forces imposed on a modeled skeleton generates joint torques appropriate for forward simulation as described by Equation 1.1.
In this work, Thelen’s Hill-type muscle model is utilized. The nonlinear differential equation describing the force balance of the massless MTU is given by

$$f_{max} \left( a(t)f_{AL}(l^M)f_v(i^M) + f_{PL}(l^M) \right) \cos(\alpha) - f_{max}f_{SE}(l^T) = 0 \quad (1.2)$$

where $f_{max}$ is the maximum force at $l_{opt}$ or optimal fiber length, $a(t)$ is the activation value at time $t$, $f_{AL}(l^M)$ is the force-length scalar based on the relative length of the MTU’s contractile element as seen in Figure 1-4a, $f_v(i^M)$ is the scalar based on the contractile element’s current velocity as seen in Figure 1-4b, $f_{PL}(l^M)$ is the contribution from the parallel elastic element, $\alpha$ is the pennation angle of the muscle fibers, and $f_{SE}(l^T)$ is the force of the series elastic element as seen in Figure 1-4c.

To summarize the transfer function terms physiologically, the force-length scalar describes the ability of the MTU to generate force when it is at lengths that are not its optimal. Muscles have a finite stroke length due to the finite area of molecular actin and myosin interactions which generate tension in the contractile element, and
changes in length reduce this interaction area. The force-velocity scalar describes the velocity-sensitive rate of cross-bridge attachment for actin and myosin. The parallel elastic element describes the contributions from the structural components of muscle membranes, and the series elastic element represents the tendon elasticity. A thorough physiological explanation for these values can be found in [9].

Importantly for this work, a distinction is made between muscle activation $a(t)$ and neural excitation $u(t)$. The transformation from $u(t)$ to $a(t)$ describes cellular calcium release and diffusion dynamics when $u(t) > a(t)$, and calcium uptake dynamics when $u(t) < a(t)$. For the experiments in this work, surface electromyography was processed into an estimated $u(t)$ signal to allow for adjustment of the activation and deactivation time constants associated with the transformation.

1.3 The Agonist-Antagonist Myoneural Interface

The development of the agonist-antagonist myoneural interface (AMI) marks one of the few major lower limb amputation paradigm shifts since the Civil War era [10]. While amputation surgery is a broad area covering a large number of limbs and conditions, the potential advantages of the AMI can be understood through comparison with standard transtibial amputation as it is most commonly performed today.

1.3.1 Transtibial Amputation

Transtibial amputation is any limb removal between the knee and ankle which transects the tibia. In the standard procedure starting with an intact limb (not always guaranteed), a primary incision creates a posterior flap of tissue from the gastrocnemius and soleus muscles as seen in Figure 1-5. This flap is cut to maximize skin length to prevent suture tension when it is eventually closed over the distal end of the residuum. While the flap is still open, the tibia and fibula are cut to preserve as much length as possible, a factor that is known to improve long-term outcomes associated with gait symmetry and musculoskeletal health. The bone ends are filed
to remove sharp protrusions, and the fibula is shortened another 1 to 2 cm proximally to avoid creating a pressure point when seated into a prosthetic socket. Nerve ends are pulled distally before being further transected and placed in a location with minimal expected tension and scarring. Muscle ends are shaped, folded over, and tied or otherwise anchored to connective tissue and bone before the posterior tissue flap is sutured to the anterior incision line [11].

Figure 1-5: The standard transtibial amputation restructures residual lower leg musculature and tissue to provide protection to distal bone ends and padding for prosthetic socket use. Reproduced with permission from Springer Nature.

Because alpha motor neuron innervation is generally preserved, the person with amputation is able to activate and contract residual musculature. However, perception of afferent feedback varies from pain and numbness to phantom limb sensation and is decidedly dissimilar from intact physiology [12]. From the mechanical perspective, the activated agonist is in series with the effectively infinite impedance of the anchored sutured end, and no antagonist feedback can be generated in this arrangement. Admittedly, though studies have been performed to characterize the cutaneous
and proprioceptive sensation of the traditional transtibial residuum \[13\], there are no known studies that have quantitatively measured isolated afferent signal generation to verify if the previous mechanical argument is responsible for the erroneous afferent sensations. The following section proposes a method which restores a physiologically relevant agonist-antagonist configuration in the residual musculature that may also alleviate some of these symptoms through generation of natural proprioception related to agonist-antagonist stretch.

### 1.3.2 Restoration of Relevant Proprioception

The AMI is a surgical construct that distally connects portions of two natural agonist and antagonist muscles in series through a harvested synovial canal. The agonist-antagonist pair is able to move freely through the anchored canal which acts as a fixed pulley. When one muscle in the pair is activated, its contraction creates tension and corresponding stretch in the antagonist. Because the AMI is joined in the center by residual tendons from both muscles, muscle spindle and golgi tendon afferents are simultaneously generated from both agonist and antagonist \[14\]. This contrasts significantly with the infinite impedance encountered by muscles in the standard transtibial amputation. Two AMIs constructed within a transtibial residuum can be seen in Figure 1-6.

The AMI was first conceptualized as a method for bidirectional communication with active prostheses. Because it is possible to simultaneously read electromyographic activity from the interface while the user receives proprioceptive feedback, it was hypothesized that a reasonable mapping could be achieved between phantom limb perception and forward control of an active prosthesis. Case studies have shown early evidence that after some training, AMI users can effectively understand AMI proprioceptive force, length, and velocity feedback signals to more accurately modulate their muscle activations for a given task compared to a control group of persons with standard amputation \[15\]. In the other direction, because AMIs remain mechanically uncoupled from the outside environment, artificially providing feedback is necessary for conveying contact dynamics in a biomimetic manner. To this end,
there is promising evidence showing relevant differentiation of force feedback through functional electrical stimulation of AMI pairs [16]. Additionally, optogenetic stimulation of muscle activation triggered by single wavelengths of light has been proven in animal models [17].

1.3.3 Dynamic Model of the AMI

Just as physically intact agonist and antagonist muscles are able to independently modulate net torque and stiffness about a rotational axis by varying activation and
coactivation, AMI pairs should be able to independently modulate net force and stiffness in a linear domain. The mechanical model of Figure 1-7 representing major AMI components demonstrates the similarity in structure.

Figure 1-7: Agonist-antagonist configuration of two Hill-type muscles with parallel elasticity and point mass. Reproduced with permission from John Wiley and Sons [18].

However, it is currently uncertain whether users truly perceive proprioception from the AMI as representative of intact limb movement. Even if all the proprioceptive pieces can be accounted for by the model, nothing can be said about what values the model parameters must be in a real AMI to convince the user it is anything but two formerly intact muscles tied together. An intact limb also possesses much greater dimensionality in terms of number of muscles and number of states necessary to describe its internal physical system. It is uncertain if this level of complexity must be matched for the AMI user to acquire a full sense of embodiment when controlling an active prosthesis.
1.4 Kinematic Characteristics of Volitional Motor Control

In the early 1980s when Japan’s precision automation made it the most efficient automobile manufacturer in the world [19], there was still no bipedal robot that could walk convincingly at even normal speeds [20]. It was perhaps this superior dexterity and robustness of human motion compared to even state-of-the-art robots of the era which encouraged biomechanics researchers to explore a prominent question regarding human movement, namely: How can control and organization of movement be explained from the interactions between human perception and the neuromusculoskeletal system [21]?

1.4.1 Stereotypical Velocity Profiles

To elucidate this connection between wetware and kinematics, biomechanicists have given special attention the stereotypical bell-shaped velocity profiles which result from volitional motions. Morasso, Abend, and Bizzi first reported velocity profiles of the human hand as being generally invariable to starting position and joint angle configuration for various straight reaching motions [22],[23]. These three researchers proposed possible explanations for this stereotypical velocity profile based on high level organizing principles decided by the central nervous system or the anatomical arrangement of muscles and joints, but did not investigate in detail at the time. Today, there are two main opposing model types, referred to as kinematics-oriented models and dynamics-oriented models, that are used to explain volitional motor behavior and velocity profile observations [24]. Key arguments for both are detailed below.

Kinematics-oriented Models

In kinematics-oriented models, human motor control is a three-tiered system composed of trajectory formulation, dynamic primitives mapping, and muscle activation in descending hierarchical order. Under this paradigm, trajectories are planned cor-
responding to task space variables external to our bodies while force disturbances Experienced during realization of those trajectories are compensated for via joint space variables. The significance of the previous discoveries lies in the fact that complex human movement was sufficiently summarized by a reduced order model that was not only descriptive, but also generative.

This class of kinematics-oriented models developed from early analysis of hand velocity profiles when it was suggested that planar horizontal reaching motions involving the shoulder and elbow joints follow trajectories which can be described as maximally smooth. In other words, for point-to-point motions of the hand, the time integral of its mean-squared jerk (time derivative of acceleration) trajectory is minimal for the functionals over the duration of the movement according to

\[ C(x(t), y(t)) = \frac{1}{2} \int_0^{t_f} \left( \left( \frac{d^3 x(t)}{dt^3} \right)^2 + \left( \frac{d^3 y(t)}{dt^3} \right)^2 \right) dt \] (1.3)

where \( C \) is the cost to be minimized, \( t_f \) is the movement end time, and \( x(t) \) and \( y(t) \) are the Cartesian coordinates of the position trajectory.

![Figure 1-8: Reaching experiment setup used by [21],[22]. Copyright 2019 Society for Neuroscience.](image)

Generation of such a minimum-jerk trajectory given time interval of movement, start position, and end position can be done by separately finding \( x(t) \) and \( y(t) \) which satisfy the Euler-Poisson equation

32
\[
\frac{\delta L}{\delta x} - \frac{d}{dt} \left( \frac{\delta L}{\delta x} \right) \ldots + (-1)^n \frac{d^n}{dt^n} \frac{\delta L}{\delta (x^n)} = 0 \tag{1.4}
\]

where \( L \) is the integrand of \( 1.3 \), \( n \) is the greatest degree of differentiation in \( L \), and \( x \) in this case is any function of time that is continuously differentiable at least \( 2n \) times in the specified time interval. A thorough treatment has been provided by Flash and Hogan \[21\] which, after assuming static kinematic boundary conditions, yields a minimum-jerk trajectory per coordinate of the form

\[
x(t) = x_i + (x_f - x_i) \left( 10 \left( \frac{t}{d} \right)^3 - 15 \left( \frac{t}{d} \right)^4 + 6 \left( \frac{t}{d} \right)^5 \right) \tag{1.5}
\]

where \( x_i \) is initial position, \( x_f \) is final position, and \( t \) is current time point within the movement of duration \( d \).

In the same publication, Flash and Hogan extended the minimum-jerk criterion to explain curved trajectories for reaching motions which include an intermediate position target. Because smoothness is an invariable feature of both straight and multiple-point hand trajectories affine relative to the global axes of the workspace \[22, 23, 25\], planning for reaching motions in terms of end effector variables as opposed to joint variables remains a strong hypothesis.

However, knowledge of joint variables is necessary to compensate for external force disturbances when realizing minimum-jerk reaching motions. Shadmehr and Mussa-Ivaldi \[26\] demonstrated this elegantly with another planar horizontal reaching experiment, now with imposed velocity-dependent force fields that were either invariant to the global position of the workspace or to the relative angular positions of the elbow and shoulder. The latter setup is shown via Figure \[1-9\].

Shadmehr and Mussa-Ivaldi highlighted several important phenomena regarding disturbed reaching motions. A non-exhaustive list follows:

1. Subjects produced minimum-jerk trajectories with no force disturbances applied, but demonstrated significant deviations from these trajectories when disturbed while still eventually reaching the target positions.
Figure 1-9: Reaching experiment with disturbance force vectors generated for point-to-point reaching motions assuming minimum-jerk trajectories in joint angle invariant forcefields. A) Disturbance forces anticipated in the left workspace of B) the experimental setup. C) Disturbance forces anticipated in the right workspace. Copyright 2019 Society for Neuroscience.

2. Subjects were able to compensate for invariant force disturbances after training over hundreds of trials, returning to trajectories closely resembling the minimum-jerk trajectories in the undisturbed condition. The learning rate remained positive but monotonically decreased with increasing numbers of trials.

3. Subjects demonstrated residual compensatory behavior from repeated exposure to force disturbances when attempting to move in the same workspace without disturbances.

4. When trained in the right workspace of Figure 1-9B with force disturbances generated from the underlying velocity-dependent forcefield of Figure 1-9C, subjects demonstrated completely dissimilar and non-smooth trajectories when suddenly moved to the left workspace and subjected to the same forcefield.

5. When trained in the right workspace of Figure 1-9B with force disturbances generated from the underlying velocity-dependent forcefield of Figure 1-9C, subjects demonstrated similar minimum-jerk trajectories when suddenly moved to the left workspace and subjected to the forcefield underlying Figure 1-9A.

6. Subjects with no visual feedback during these experiments demonstrated similar behavior to subjects with visual feedback.
Consideration of points 4 and 5 together provided significant evidence of compensatory motor learning behavior based on joint variables rather than task space variables. In other words, a roughly 45° counterclockwise rotation at the shoulder and a similar rotation of the forcefield in the translated workspace allowed subjects to reproduce similarly smooth trajectories. If instead compensatory behavior were task space dependent, similarly smooth trajectories would be generated with collocated translation of the work space and unrotated forcefield.

While the minimum-jerk hypothesis is remarkable for mathematically generating these results which agree with observed reaching kinematics in a dimensionally-reduced manner, it alone does not sufficiently explain how the body as a biological entity produces these trajectories.

In 2000, Mussa-Ivaldi and Bizzi proposed a model of motor learning and actuation using the idea of dynamic motion primitives [27]. These motion primitives are distinct spatially varying forcefields that are uniquely activated via discrete modules formed by premotor circuits in the spinal cord. They were shown to be capable of being vectorially added to produce virtual trajectories consistent with Hogan’s [28] well-known paradigm of impedance control. As a demonstration of the explanatory ability of dynamic motion primitives, the authors were also able to recreate the undisturbed and disturbed reaching trajectories of Shadmehr and Mussa-Ivaldi [26] using only four primitives, generating bell-shaped velocity profiles in the process. Details are shown in Figure 1-10.

Importantly, the notion of dynamic motion primitives was supported by previous work observing the hindlimb forcefields generated by selective spinal stimulation in rats and frogs [29], [30], providing a holistic view of organizing principles as a result of biological processes.

Dynamics-oriented Models

In dynamics-oriented models, human motor control is instead sufficiently described by coded patterns based on neural biology, muscle state, and mechanical properties [31]. These codes have been presented as any number of piecewise or continuous
mathematical functions, linear and nonlinear, that generate speed, force, or oscillation.

Plamondon’s support-bounded log-normal function (lgnb) comes from one such model that has demonstrated superior velocity profiling abilities compared to many other kinematics- and dynamics-oriented models. Its form is derived from the interactions of a synergistic agonist-antagonist neuromuscular system where each muscle’s individual motor components have both highly parallel and highly hierarchical shared activation inputs, as shown in Figure 1-11.

Plamondon states that if the individual impulse responses from each module of type $h(t)$ can be linearly superimposed, and if each module experiences an activation time delay relative to its immediately superior module, then the time delay $T_n$ for the $nth$ module in the sequence can be expressed as
Figure 1-11: Agonist-antagonist muscle system which accepts delayed activation impulses $U(t - t_0)$ of some magnitude $D$ and outputs end effector velocity $V_\sigma(t)$ after filtering through cascaded modules of type $h(t)$. Reproduced with permission from Springer Nature [33].

$$T_n = (1 + \epsilon_1)(1 + \epsilon_2)(1 + \epsilon_3)...(1 + \epsilon_n)T_0$$  \hspace{1cm} (1.6)

where $T_0$ is an arbitrary time reference and $\{\epsilon_j | j \in \mathbb{N}, j < n\}$ is the set of all previous random time delays. If additionally the impulse responses are non-negative functions, $n$ is sufficiently large, and each response has finite variance, then the central limit theorem predicts $V_\sigma(t)$ will be log-normal in shape. Bounding the support of this log-normal function ensures velocity at the end of movement is zero, and the resultant lgnb function is defined as

$$V_\sigma(t) = \frac{D(t_1 - t_0)}{\sigma \sqrt{2\pi}(t - t_0)(t_1 - t)} \exp \left\{-\frac{1}{2\sigma^2} \left[\ln \frac{(t - t_0)}{(t_1 - t)} - \mu\right]^2\right\}$$  \hspace{1cm} (1.7)

where $D$ is total displacement of the movement, $t_0$ the time of the impulse command, $t_1$ the end time of the movement, $\mu$ and $\sigma^2$ the mean and variance of $\ln(t - t_0)$. A thorough derivation may be found in [32].

Determination of the descriptive parameters $D$, $t_0$, $t_1$, $\mu$, and $\sigma$ for a given movement can be performed computationally through iterative nonlinear least squares re-
gression, resulting in close agreement with recorded velocity profiles as seen in Figure 1-12. Compared to minimum-jerk, the form of lgnb is capable of describing the skew observed in many wrist velocity profiles while the objective function of minimum-jerk limits it to symmetric solutions. However, the generative form of minimum-jerk seen in Equation 1.5 allows trajectories to be planned in advance while lgnb is purely descriptive. This fact alone raises questions about the sufficiency of similar dynamics-oriented models in describing formulation of movement. A parallel line of questioning regarding sufficiency of velocity profile analysis itself is raised when considering the uniqueness of handwriting, even between identical twins [34]. Though invariances between individuals should exist for any given task on some level, what is the limit of their ability to explain motor control even one level up the cognitive hierarchy?

Figure 1-12: Reconstructed velocity profile (solid line) with parameters $D = 1.990, t_0 = 0.6195, t_1 = 0.7735, \mu = -0.162, \sigma = 0.8325$. Reproduced with permission from Springer Nature [24].
Differences in modeled stereotypical velocity profiles of human motion and the biological processes underlying their generation may also depend on the specific joints and limbs involved. It is critical to note that the experiments which preceded formulation of the kinematics-oriented minimum-jerk hypothesis and the dynamics-oriented lgnb function were fundamentally different. Upper limb reaching experiments performed by Flash and Hogan \[21\] involved multiple joints connecting body segments with significant mass moving the hand over distances of 20 - 40 cm while the trajectories analyzed by Plamondon et al. \[35\] involved only the wrist and fingers moving distances of 4 cm.

### 1.4.2 Speed-Accuracy Tradeoff

Another hallmark of human motion is the speed-accuracy tradeoff. It is a relationship first quantified by Paul Morris Fitts \[36\] and described mathematically as

$$ID = \log_2\left(\frac{2D}{W}\right) \tag{1.8}$$

where $ID$ is the index of difficulty in bits, $D$ is the linear distance from starting point to target, and $W$ is the width of the target along the axis of motion. $ID$ can be related to movement time in terms of throughput (information per unit time) by

$$TP = \left(\frac{ID}{MT}\right) \tag{1.9}$$

where $MT$ is average time to complete the movement.

When 1.8 and 1.9 are taken together, average time required to complete a movement can be directly related to target size and distance to target

$$MT = a + b\left\{\log_2\left(\frac{2D}{W}\right)\right\} \tag{1.10}$$

where $a$ and $b$ are empirically determined constants based on regression analysis of a given task’s data. This basic form of Fitts’s Law has been successfully adapted to account for observed limitations in human motor performance across many tasks,
even serving as the prime reason for selection of the computer mouse as the preferred method of interaction with a digital display [37]. Though the explanatory power of Fitts’s Law does not scale as any one of the temporal or physical parameters is tested at extreme ranges, it remains an easily interpreted metric used to quantify certain empirical observations of motor behavior without expounding underlying biomechanical causes.

Michmizos and Krebs [38] have investigated discrete ankle-foot pointing with analysis based on Fitts’s Law, concluding that movement time was highly correlated with ID in both DP and IE directions while peak velocity remained relatively constant. Additionally, while increasing ID did not change the value of maximum velocities observed, it did reduce the average velocity for the movement due to the presence of slower, corrective submovements near the target to correct for overshoot and undershoot.

A study on rhythmic upper limb motions by Park et al. [39] also demonstrated the existence of characteristic preferred movement times, indicating a limit where humans no longer generate smooth motion with further reductions of velocity. In the study, movements of a given displacement which were slower than the preferred time showed evidence of being composed of multiple submovements while movements at the preferred time and faster demonstrated single lgnb velocity profiles. It was the fact that submovements themselves could also be described by multiple overlapping lgnb functions which provided evidence of dynamic motion primitives which are linearly composable.

1.4.3 Coordination of Bimanually Symmetric Movement

A study by Mechsner et al. [40] investigated subtleties of human motor control during bimanual coordination tasks. The researchers discovered that coordination of upper limb movement involving both sides of the body was largely dependent on visual perception rather than any sort of variables related to internal body state. They demonstrated this phenomenon primarily through three tests, two of which are described here.
The first test revisited the bimanual finger coordination studies well-known in the field from a slightly different perspective [41], [42]. The test conditions are shown in Figure 1-13.

The original test requires participants to adduct and abduct their index fingers in rhythm with a metronome while the tempo increases. Participants are instructed to maintain their hands in the orientation of Figure 1-13C while performing periodic symmetric (Figure 1-13A) or parallel (Figure 1-13B) motions. As the tempo increases, participants generally converge on the symmetric pattern regardless of the pattern with which they begin. Early hypotheses proposed the results indicated preference for activation of homologous muscles [41], while variations of the test involving flexion and extension of ipsilateral limbs suggested easier coordination when moving in the
same direction regardless of actual muscles used [13].

It was Mechsner et al. who performed the test with all four orientations shown in Figure 1-13. For all conditions, symmetry was either maintained or adapted as tempo increased. This definitively disproved the proposal that symmetry arose from preferred activation of homologous muscles. To emphasize the importance of visual perception of task space variables, they designed another test shown in Figure 1-14.

![Figure 1-14: A) Experimental setup requiring separate instrument rotation through different transmission ratios B) In-phase condition C) Anti-phase condition. Reproduced with permission from Springer Nature [40].](image)

In the setup above, the left flag above the divider circles at a 1:1 ratio with the left hand while the right flag circles at a 4:3 ratio with the right hand. Earlier tests demonstrated that explicitly attempting to rotate left and right hands at a 4:3 ratio was nearly impossible. With the experiment, it was found that participants were able to easily maintain the in-phase condition by observing the flags, thereby achieving a 4:3 rotational frequency between left and right hands.
1.5 Background Summary

With the introduction of the AMI comes a new research platform ready for exploration. However, it remains to be determined if this construct is intuitive and advantageous for control of a modeled limb or active prosthesis beyond the capability of persons with standard amputation. To provide hope for the endeavor, numerous studies on upper limb coordination and volitional movement have suggested the human ability of reducing complex trajectories into simple task space representations which are then carried out by lower levels of muscle control. From the mechanical perspective, the AMI should generate a descriptive set of sensory feedback through relevant proprioceptive signals which more accurately informs these lower level controllers of its state in time. Though each AMI is only one muscle pair which does not compare to the redundancy of intact human musculature, it is perhaps just enough to draw the map between intent and actuation.
Chapter 2

Coordination and Control Utilizing the Agonist-Antagonist Myoneural Interface

This thesis aims to quantify the volitional coordination capabilities of the agonist-antagonist myoneural interface (AMI) for applications related to control of active prostheses. In the first section, bilateral rhythmic coordination of ankle and subtalar movements is investigated in a control group of physically intact human subjects to characterize stereotypical kinematics of volitional lower limb movement. Subsequently, neuromusculoskeletal (NMS) modeling techniques are developed to directly map estimated neural excitations from agonist-antagonist myoneural interface musculature to intended subtalar inversion and eversion kinematics.

In a case study, the developed neuromusculoskeletal modeling techniques are applied to optimize a dynamic subtalar model for use by a unilateral subject with amputation possessing the agonist-antagonist myoneural interface. The subject’s subsequent performance in bilateral rhythmic coordination utilizing the model and her own intact subtalar demonstrates the capacity of the agonist-antagonist myoneural interface to coordinate with intact anatomy in a biomimetic manner.
2.1 Contributions

Characteristics of Intact Lower Limb Movement

Preliminary evidence supports the following hypotheses regarding characteristics of intact lower limb movement:

- Bilateral rhythmic coordination of subtalar inversion-eversion (IE) demonstrates greater stability in the symmetric rather than the parallel pattern as frequency increases, agreeing with findings on bimanual coordination.

- Symmetric rhythmic coordination of ankle dorsiflexion-plantarflexion (DP) is less variable than subtalar IE with respect to relative phase within a given frequency, suggesting greater volitional control of DP over IE.

- Rhythmic IE motions demonstrate stereotypical velocity profiles, agreeing with findings on coordination of upper limb movements.

- There are no significant differences observed between sighted and blind conditions in rhythmic coordination of IE.

- Evidence is shown of movement amplitude and effective target width varying in accordance with Fitts’s Law as frequency of rhythmically coordinated movements increases.

AMI Control of the Optimized Neuromusculoskeletal Subtalar Model

Preliminary evidence supports the following statements regarding AMI control of the optimized neuromusculoskeletal subtalar model:

- Bilateral rhythmic coordination of IE involving the optimized NMS model and intact subtalar also demonstrates greater stability in the symmetric rather than parallel pattern.

- The optimized NMS model is general enough to achieve movement frequencies beyond the one used for optimization while respecting human bandwidth limitations predicted by Fitts’s Law.
The optimized NMS model generates velocity profiles that differ significantly from those of an intact subtalar, though subsequent analysis suggests pathways for improvement.

2.2 Methodology

2.2.1 Subjects

Physically intact female subjects \((n = 4)\) were recruited for the control group, averaging \(21 \pm 1\) years old, \(1.62 \pm 0.05\) m, and \(73 \pm 12\) kg (mean ± standard deviation). A single female, Subject BKA (below knee AMI), who possesses two AMI pairs through elective unilateral transtibial amputation was also recruited (42 years old, 1.68 m, 85 kg). One pair was constructed from her tibialis anterior (TA) and lateral gastrocnemius (LGAS) for primary control over ankle DP. A second pair was constructed from her tibialis posterior (TP) and peroneus longus (PL) for primary control over subtalar IE. All subjects were right foot dominant and had normal vision. In a precheck questionnaire, all subjects indicated no physiological disorders which would affect their ability to control movement of their intact ankle-foot joints. Experiments were conducted with informed consent at the Massachusetts Institute of Technology (MIT) Media Laboratory under the approval of the MIT Committee on the Use of Humans as Experimental Subjects.

2.2.2 Apparatus and Signals Processing

For all experiments, surface electromyography (sEMG) signals and ankle-foot kinematics were collected from subjects. An electromechanical relay was used to synchronize recorded data in time.

sEMG

A commercial Refa (TMSi, Oldenzaal, Netherlands) 128-channel amplifier was used to collect sEMG signals. For all subjects, the skin surface was cleaned with isopropyl
alcohol, and adhesive wet surface electrodes were placed on the dominant leg in redundant pairs over exposed locations nearest to the bellies of the following muscles: tibialis anterior (TA), medial gastrocnemius (MGAS), lateral gastrocnemius (LGAS), peroneus longus (PL), and tibialis posterior (TP). A ground reference electrode was placed on the patella of the dominant leg. For Subject BKA, additional electrodes were placed in a gridlike pattern over the estimated locations of the four muscles which compose her two AMI pairs. 1.5 m shielded cables connected each electrode terminal to the Refa amplifier.

Figure 2-1: Clusters of four wet surface electrodes were placed over each AMI muscle. Pictured are the PL cluster (left) and TA cluster (right). Antagonist muscles for both are located medially on the residuum.

For each trial, monopolar sEMG signals were recorded at a sampling frequency of 2,048 Hz. Bipolar signals were reconstructed for each muscle after data collection. A fourth order 10 - 500 Hz band pass infinite impulse response (IIR) Butterworth filter was designed in MATLAB 2019a and applied forward and backward over each recording. Filtered data were then rectified and normalized against the maximum voltage within each recording, assumed to represent maximum voluntary contraction (MVC). Then, a fourth order 10 Hz low pass IIR Butterworth filter was applied forward and backward to produce a record of neural excitation $\mu(t)$. See Buchanan et al. [44] for details on this sEMG processing procedure. For experiments involving
NMS model optimization, sEMG recordings were level shifted so that the minimum excitations across the entire trial were 0.01 to satisfy Thelen Hill-type muscle tendon unit (MTU) constraints [9].

Though sEMG was recorded from all intact subjects, the data are not reported here.

**Ankle-foot Kinematics**

A pair of commercial two-axis goniometers (Biometrics Ltd., Newport, UK) was used to measure ankle-foot kinematics. Subjects were required to wear well-fitted athletic shoes. For each goniometer, one end was adhered to the heel of the shoe while the other was adhered to skin superior the Achilles tendon. Goniometers were calibrated for measurement axis and motion axis parallelism by instructing subjects to perform slow, controlled motions while adjusting the positioning of the sensors. Subjects were carefully guided to compensate for the naturally oblique DP axis of rotation during this portion. Afterward, goniometer ends were further secured to the shoe and shank using porous medical tape.

All ankle-foot position trajectories were recorded at a sampling frequency of 1,000 Hz. A fourth-order 5 Hz low pass IIR Butterworth filter was applied forward and backward over the raw trajectory data. Velocity trajectories were generated from the filtered position trajectories by two-point forward finite differentiation.

### 2.2.3 Bilateral and Unilateral Coordination Tasks

With inspiration from Mechsner et al.’s bimanual coordination [40] and Park et al.’s rhythmic reaching studies [39], all subjects were asked to complete a series of rhythmic tasks involving ankle DP and subtalar IE to determine characteristics and limitations of lower limb coordination. Subjects were seated on the edge of a patient bed with knees at 90° flexion. sEMG electrodes and goniometers were attached as described in the previous section. Each trial required subjects to perform one cyclical motion per downbeat of a pre-recorded metronome soundtrack. The one minute soundtrack
Table 2.1: Experimental Conditions for Ankle-foot Coordination Tasks

<table>
<thead>
<tr>
<th></th>
<th>Bilateral</th>
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<th>Unilateral</th>
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<tbody>
<tr>
<td></td>
<td>Symmetry</td>
<td>Parallel</td>
<td>Sagittal</td>
<td>Sagittal</td>
</tr>
<tr>
<td>Vision</td>
<td>BiVisSym</td>
<td>BiVisPar</td>
<td>BiVisSag</td>
<td></td>
</tr>
<tr>
<td>Blind</td>
<td>BiBlindSym</td>
<td>BiBlindPar</td>
<td>BiBlindSag</td>
<td>Vision</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>UniVisIE</td>
</tr>
</tbody>
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consisted of five equal duration sections starting at a tempo of 1 Hz in the first section and incrementing by 0.4 Hz until a final tempo of 2.6 Hz.

Bilateral tasks required movement of all ankle-foot joints while unilateral tasks required movement of the dominant ankle-foot joints only (Subject BKA performed unilateral tasks on both sides). Tasks with vision required participants to look at their feet while blind tasks were performed with eyes closed. In the symmetry condition, subjects were asked to invert both subtalars on the downbeat and evert both subtalars on the (silent) offbeat. In the parallel condition, subjects were asked to evert the left subtalar and invert the right subtalar on the downbeat and to mirror the motion on the offbeat. In the sagittal condition, subjects were asked to plantarflex on the downbeat and dorsiflex on the offbeat. In the IE condition, subjects were asked to invert on the downbeat and evert on the offbeat. Subjects were asked to go the full range of motion for all movements. Subjects completed three trials for each condition in random order with a two minute break between trials to limit fatigue.

At the end of every trial, subjects performed a slow, controlled range of motion calibration test consisting of two DP cycles followed by two IE cycles to address offset errors from goniometer taring. For Subject BKA in particular, each trial’s ankle-foot trajectories were then vertically translated to center the calibration range of motion with average range of motion of an age- and gender-matched group from literature [45] using

$$\theta_{shift, trial} = \frac{\theta_{max, ref}}{\theta_{max, ref} - \theta_{min, ref}}(\theta_{max, trial} - \theta_{min, trial}) - \theta_{max, trial}$$  \hspace{1cm} (2.1)

This was done assuming Subject BKA’s relative ranges of motion in all directions from the neutral position were proportional to those reported in literature.
The entirety of the combined conditions tested is shown with referral names in Table 2.1. For all conditions, subjects were instructed to do their best to remain in time with the metronome downbeats. They were given explicit permission to switch to any other bilateral pattern if necessary to do so. All subjects were naive to the nature of the study.

Though unilateral tests were performed, the data are not reported here.

**Relative Phase**

To quantify degree of coordination during bilateral tasks, the metric of relative phase is borrowed from experiments on bimanual coordination. For each DP or IE half cycle, it is possible to normalize each joint’s angular position and velocity against its own maximums within the half cycle. Figure 2-2 demonstrates this visually on two unit circles.

![Relative phase angles between left and right joints in the middle of a movement. Adapted from Mechsner et al. [40].](image)

Dorsiflexion and inversion are treated as positive directions for their respective rotational axes. For each half cycle considered, relative phase was calculated by noting the time index of the right joint at its downbeat inflexion point (either maximum inversion or maximum plantarflexion) and calculating the phase of the left joint. If both joints remain perfectly symmetric, relative phase is $0^\circ$ throughout the movement. If both are perfectly parallel during IE, relative phase is $180^\circ$. Values that are lower
for either condition imply a lagging left joint while greater values imply a leading left joint. A generalized formula for relative phase is given as

\[
\theta_{rel} = \phi_R - \phi_L = \tan^{-1}\left(\frac{\dot{\theta}_R}{\theta_R}\right) - \tan^{-1}\left(\frac{\dot{\theta}_L}{\theta_L}\right)
\]  

(2.2)

where \(\theta_R\) and \(\theta_L\) are normalized angular positions and \(\dot{\theta}_R\) and \(\dot{\theta}_L\) are their respective normalized angular velocities.

Half cycles for analysis were taken from a continuous middle portion of each frequency band to avoid transient motions during tempo changes. A total of 77 half cycles per frequency across all control subjects were used to calculate relative phase per test condition. Samples were binned into containers 15° in width, normalized by the number of all samples within a frequency band, then plotted as surfaces to visualize distribution.

**Velocity Profile Analysis**

Average velocity profiles were extracted and analyzed for characteristic features of rhythmic subtalar movement. For 1.4 Hz and 2.2 Hz frequencies, time-normalized right subtalar velocity profiles from maximum eversion to maximum inversion were averaged across all control subjects for biVisSym and biBlindSym conditions. Skewness and kurtosis were calculated for all individual velocity profiles. The beginning and end indices for each movement half cycle were determined by detecting when speed rose above and fell below 3% of the maximum movement velocity. A lgnb velocity trajectory was generated using an iterative least squares curve fit solver with Equation 1.7. Coefficients of determination were calculated for the generated lgnb velocity profiles. Standard deviations of the average velocity profiles were calculated and graphed per normalized time point. These techniques were inspired from a study on discrete volitional ankle-foot movements by Michmizos et al. [46].
Human Control Bandwidth

For all subjects, movement amplitudes and actual movement frequencies were calculated per IE half cycle for all frequencies and all trials in the biBlindSym condition. Movement amplitudes were determined from integrating the velocity profiles found earlier with respect to time, and actual movement frequencies were calculated as the inverse of double the duration of half cycle movement time.

Linear regression was performed on all scatter plots of movement amplitude versus actual movement frequency to qualitatively check for consistency with Fitts’s Law. $\frac{2D}{W}$ values were calculated by defining

\[ D \equiv \bar{D} \]  \hspace{1cm} (2.3)

and

\[ W = W_e \equiv 4.33\sigma_D \]  \hspace{1cm} (2.4)

for a small band of actual movement frequencies where $\bar{D}$ is simply the average movement amplitude and $W_e$, effective width, is set to account for 96% of the variation of $\bar{D}$ in the band [47]. A frequency bin bandwidth of 0.03 Hz was used with the requirement that at least 5 samples existed before a valid ID value could be extracted.

2.2.4 NMS Model Parameter Optimization

Dynamic Model of Subtalar Inversion-Eversion

A simplified NMS dynamic model was developed to find a valid mapping between Subject BKA’s AMI excitations to the physical domain of subtalar IE kinematics. IE was chosen as it allowed for comparison of bilaterally symmetric and parallel coordination with the physically intact control group. Design choices for this model were made from the suppositions that:

1. All models are wrong, but some are useful. A model should be sufficiently complex to describe key behavior, but additional complexity obfuscates insight.
2. Estimation of the state of physical AMI pairs is complex and unnecessary for control of task space variables. In other words, an AMI user can control a dynamic model by formulating movement trajectories in task space variables.

3. Intact lower limb NMS morphological parameters should be respected when possible, but scaling to avoid high degrees of decimal precision is preferred for representation and computation.

![Figure 2-3: Simplified 2D IE dynamic model with passive rotational stiffness $k$, rotational damping $b$, mass $m = 0.4$ kg, and two Hill-type MTUs in agonist-antagonist configuration. $l_1 = 0.7$ m, $l_2 = 0.2$ m, $l_3 = 0.1$ m. Figure not drawn to scale.](image)

Referring to the model drawn in Figure 2-3, $l_1$ was chosen to be 0.7 m, a relatively large value due to finite muscle-tendon unit (MTU) stroke length. The actuators need to be effective over the entire natural IE range of motion considering contractile element optimal fascicle length and active force curve shape. The TP and PL AMI muscles’ excitations were used for input due to early findings suggesting the ability of AMIs to preserve proprioception and afferent excitation patterns related to their original intact musculature. A rotational domain was chosen over a linear one to allow effective MTU moment arms to vary over the range of motion in a physiologically relevant manner [48]. As IE deviates from zero, effective MTU moment arms decrease according to Figure 2-4 and the relative effectiveness of passive restoring stiffness, modeled after ligament contributions, increases. Damping is modeled to represent energetic losses due to tissue sliding surfaces. Point mass $m$ has a moment of inertia $J = 0.016 \text{ kg} \cdot \text{m}^2$ about the pivot which is greater than that of a normal foot [49].
This was done to allow MTU morphological parameters to vary over a larger “human-readable” absolute range during optimization.

Figure 2-4: MTU lever arm lengths for both the TP and PL vary with IE angle.

A bond graph modeling both MTUs as a single ideal effort source through a modulated transformer is shown in Figure 2-5. On inspection, the system is second-order by virtue of its two independent energy storage elements and is capable of natural oscillatory behavior. The transfer function relating MTU activation to tension force developed has previously been detailed in Section 1.2.4.

Figure 2-5: Bond graph of the entire system with effective MTU lever arm expressed as a modulated transformer.
Including state variables for the MTUs, dynamics of the system are given by

\[ J\ddot{\theta}_{IE} = \left( F_{TP}(\alpha_{TP}, l_{TP}, v_{TP}) - F_{PL}(\alpha_{PL}, l_{PL}, v_{PL}) \right) l_3 \cos(\theta_{IE}) - b\dot{\theta}_{IE} - k\theta_{IE} \quad (2.5) \]

**Genetic Algorithm Implementation**

As MTU force production is highly sensitive to morphological parameters for any given muscle activation, a global optimization problem was formulated to best relate estimated AMI neural excitation inputs to desired subtalar IE outputs. All input data used were taken from a three second window in the 1.4 Hz section of Subject BKA’s biBlindSym trials. From this window, raw AMI sEMG data from the residual TP and PL were processed according to section 2.2.2 to produce estimated AMI neural excitations \( \mu(t) \). Time synchronized IE trajectory values from Subject BKA’s intact subtalar were used as the desired reference trajectory. Figure 2-6A shows all input subject data used in the optimization. Upon initial observation, the high degree of TP and PL neural coexcitation may appear incongruous with the given task. However, this can only imply some amount of muscle coactivation and stiffness generation; further modeling is required to understand implications in the physical domain. For comparison, Figure 2-6B shows three seconds of AMI excitations and intact subtalar kinematics collected from Subject BKA during a biBlindSag trial. Alternating TA and LGAS excitation is clearly observed. Detailed analysis on the selection of these AMI excitations and intact subtalar kinematics for optimization input can be found in the discussion section.

The dynamic model was implemented in OpenSim 4.0, an open source dynamics environment widely used for NMS modeling [50], [51]. MATLAB’s genetic algorithm (GA) toolbox was used to find the global optimum values of the MTU morphological and dynamic model parameters listed in Table 2.2. MTU variables which belong to OpenSim’s Thelen2003Muscle class not mentioned were fixed to their default values. A total of 18 MTU and 2 model parameters were investigated over the ranges specified in the table. The optimal parameter set minimized the residual sum of squares between generated trajectory and reference trajectory using the single objective cost
Figure 2-6: (A) Three second window of Subject BKA’s AMI TP and PL neural excitations and intact subtalar IE trajectory during biBlindSym 1.4 Hz used as optimization input (B) Three second window of all AMI neural excitations and intact subtalar trajectories during biBlindSag 1.4 Hz

function

$$C(\theta(t), \theta_{ref}(t)) = 1 - R^2 = \frac{\sum_{t=0}^{n-1} (\theta(t) - \theta_{ref}(t))^2}{\sum_{t=0}^{n-1} (\theta_{ref}(t) - \bar{\theta}_{ref})^2}$$ (2.6)

where $t$ is the discretized time index for trajectories $n$ ms long. A general flow chart for the GA optimization can be seen in Figure [2-7]

Every GA run was uniformly initialized across the solution space with 5,000 members and set to run for 100 generations or until stalling for 3 generations. Two elite members were preserved per generation. Each iteration within the GA performed an OpenSim forward simulation with the specified AMI neural excitation inputs into a dynamic IE model set to a specific population member’s parameters and to the initial position of the reference trajectory. Three separate GA runs were performed, each taking approximately 12 hours on an AMD Ryzen™ 2920X CPU with 12 parallel processing threads. The optimized parameter set from the three runs with the best performance was used for all subsequent analysis.
Generated Trajectory Analysis

For Subject BKA, relative phase plots for biBlindSym and biBlindPar conditions were generated using the optimized dynamic model with corresponding AMI excitations from all associated trials. Velocity profile analysis was performed for biBlindSym model outputs at 1.4 Hz and 2.2 Hz using data from all trials according to the procedure described for the control group. Movement amplitudes and actual movement frequencies were also calculated for biBlindSym model outputs using data from all trials according to the procedure described for the control group.

An excitation impulse response was generated for both the optimized TP and PL muscle. Because $u(t)$ signals were normalized based on the post-trial calibration procedure detailed earlier, the impulse amplitude used was the maximum value of $u(t)$ for each muscle from the same trial as the reference trajectory. The impulse duration was 100 ms.
Table 2.2: Optimization Parameter Ranges and Initial Values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Range</th>
<th>Initial Value</th>
</tr>
</thead>
<tbody>
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<td>$F_{max}$</td>
<td>$0.05F_{max,0} \leq F_{max} \leq 6F_{max,0}$</td>
<td>800 N</td>
</tr>
<tr>
<td>$l_{opt}$</td>
<td>$0.5l_{opt,0} \leq l_{opt} \leq 1.4l_{opt,0}$</td>
<td>0.45 m</td>
</tr>
<tr>
<td>$l_{slack}$</td>
<td>$0.5l_{slack,0} \leq l_{slack} \leq 1.4l_{slack,0}$</td>
<td>0.4 m</td>
</tr>
<tr>
<td>$v_{max}$</td>
<td>$7 \leq v_{max} \leq 12$</td>
<td>$10 l_{opt}s^{-1}$</td>
</tr>
<tr>
<td>$K_{active}$</td>
<td>$0.1 \leq K_{active} \leq 0.7$</td>
<td>0.5 m</td>
</tr>
<tr>
<td>$K_{passive}$</td>
<td>$2.0 \leq K_{passive} \leq 7.0$</td>
<td>4.0 m</td>
</tr>
<tr>
<td>$A_f$</td>
<td>$0.2 \leq A_f \leq 0.7$</td>
<td>0.3 m</td>
</tr>
<tr>
<td>$\tau_{act}$</td>
<td>$0.01 \leq \tau_{act} \leq 0.08$</td>
<td>0.01 s</td>
</tr>
<tr>
<td>$\tau_{deact}$</td>
<td>$0.03 \leq \tau_{deact} \leq 0.08$</td>
<td>0.04 s</td>
</tr>
<tr>
<td>$k$</td>
<td>$0 \leq k \leq 15.0$</td>
<td>$Nm\theta^{-1}$</td>
</tr>
<tr>
<td>$b$</td>
<td>$0 \leq b \leq 2.0$</td>
<td>$Nm\dot{\theta}^{-1}$</td>
</tr>
</tbody>
</table>

2.3 Results

2.3.1 Optimal Model Parameters

The kinematic performance of the optimized model compared to the reference trajectory is shown in Figure 2-8. The corresponding optimal parameter set found from three separate GA runs can be seen in Table 2.3. Independent impulse responses for both the optimized TP and PL are shown together in Figure 2-9.

Table 2.3: Optimized Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>TP</th>
<th>PL</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_{max}$</td>
<td>2,942 N</td>
<td>66.4 N</td>
</tr>
<tr>
<td>$l_{opt}$</td>
<td>0.56 m</td>
<td>0.2584 m</td>
</tr>
<tr>
<td>$l_{slack}$</td>
<td>0.42 m</td>
<td>0.2579 m</td>
</tr>
<tr>
<td>$v_{max}$</td>
<td>$9.2124 l_{opt}s^{-1}$</td>
<td>$11.8386 l_{opt}s^{-1}$</td>
</tr>
<tr>
<td>$K_{active}$</td>
<td>0.5534</td>
<td>0.201</td>
</tr>
<tr>
<td>$K_{passive}$</td>
<td>5.9643</td>
<td>2.3</td>
</tr>
<tr>
<td>$A_f$</td>
<td>0.6942</td>
<td>0.6688</td>
</tr>
<tr>
<td>$\tau_{act}$</td>
<td>0.0783 s</td>
<td>0.0198 s</td>
</tr>
<tr>
<td>$\tau_{deact}$</td>
<td>0.0317 s</td>
<td>0.0741 s</td>
</tr>
<tr>
<td>$k$</td>
<td>1.4081 Nm$\theta^{-1}$</td>
<td></td>
</tr>
<tr>
<td>$b$</td>
<td>0.8127 Nm$\dot{\theta}^{-1}$</td>
<td></td>
</tr>
</tbody>
</table>
2.3.2 Characteristics of Bilateral Movement

Relative Phase Comparisons

Relative phase plots for Subject BKA in biBlindSym and biBlindPar generated using AMI excitations as input into the optimized model are shown in Figure 2-10. Control group DP and IE performance for the bilateral conditions in Table 2.1 are shown in Figure 2-11 where $0^\circ$ is perfectly bilaterally symmetric and $180^\circ$ is perfectly out of phase.
Figure 2-9: Independently calculated IE impulse responses for both TP and PL. TP peak amplitude of 19.83° was reached after 158 ms. PL response was negligible.

Figure 2-10: Subject BKA’s relative phase performance in blind IE conditions
Figure 2-11: Relative phase performance across all control group subjects
Averaged Velocity Profiles

Figure 2.12 shows time-normalized average velocity profiles calculated using right foot trajectory data from biVisSym and biBlindSym conditions at 1.4 and 2.2 Hz. Optimized model left foot velocity profiles are shown in the top two subfigures. Generated lgnb trajectories are overlayed on all profiles. Table 2.4 summarizes calculated metrics for all averaged velocity profiles.
Figure 2-12: Averaged time-normalized velocity profiles for select conditions. Pink diamond designates peak average velocity; vertical gray line designates normalized time midpoint.
Table 2.4: Metrics for Averaged IE Velocity Profiles

<table>
<thead>
<tr>
<th>Parameter</th>
<th>BKA Model Blind 1.4 Hz</th>
<th>BKA Model Blind 2.2 Hz</th>
<th>BKA Blind 1.4 Hz</th>
<th>BKA Blind 2.2 Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Peak Velocity (degrees/s)</td>
<td>119.60 ±31.72</td>
<td>150.68 ±46.18</td>
<td>121.52 ±28.50</td>
<td>111.80 ±41.38</td>
</tr>
<tr>
<td>Mean Skewness</td>
<td>-0.09 ±0.44</td>
<td>-0.47 ±0.42</td>
<td>-0.09 ±0.16</td>
<td>-0.49 ±0.23</td>
</tr>
<tr>
<td>Mean Kurtosis</td>
<td>1.88 ±0.44</td>
<td>2.25 ±0.42</td>
<td>1.59 ±0.16</td>
<td>2.01 ±0.23</td>
</tr>
<tr>
<td>$R^2$ lgnb</td>
<td>0.993</td>
<td>0.978</td>
<td>0.999</td>
<td>0.999</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Control Blind 1.4 Hz</th>
<th>Control Blind 2.2 Hz</th>
<th>Control Vis 1.4 Hz</th>
<th>Control Vis 2.2 Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Peak Velocity (degrees/s)</td>
<td>148.65 ±45.37</td>
<td>125.30 ±37.08</td>
<td>149.11 ±80.90</td>
<td>129.04 ±23.57</td>
</tr>
<tr>
<td>Mean Skewness</td>
<td>-0.01 ±0.26</td>
<td>-0.39 ±0.26</td>
<td>-0.052 ±0.26</td>
<td>-0.40 ±0.31</td>
</tr>
<tr>
<td>Mean Kurtosis</td>
<td>1.67 ±0.26</td>
<td>1.89 ±0.26</td>
<td>1.68 ±0.26</td>
<td>1.95 ±0.31</td>
</tr>
<tr>
<td>$R^2$ lgnb</td>
<td>0.999</td>
<td>0.999</td>
<td>0.999</td>
<td>0.999</td>
</tr>
</tbody>
</table>
2.3.3 Bandwidth Limitations

Movement amplitudes for IE half cycles in the biBlindSym condition are scattered against their calculated actual frequencies of movement in Figure 2-13. Also shown in Figure 2-13 are corresponding box plots describing the distributions of actual movement frequencies against given metronome frequencies. Plots for the control group, Subject BKA’s intact subtalar, and Subject BKA’s model output are shown in descending row order. Figure 2-14 shows the Fitts’s Law linear regression analysis performed on the binned datapoints of the scatter plot.
Figure 2-13: Rows from top to bottom: movement amplitudes and frequency distributions of IE half cycles during biBlindSym for all control subjects, Subject BKA’s intact subtalar, and Subject BKA’s model output.
Figure 2-14: General trend of Fitts’s Law linear regression on the movement amplitude and actual movement frequency data of [2-13].
2.4 Discussion

2.4.1 Characterization of Volitional Lower Limb Coordination

As observed in bimanual coordination, symmetrical bilateral coordination was found to be more stable than parallel in the control group by measure of relative phase. Borrowing again from Mechsner et al. [40], a relative phase of $0 \pm 60^\circ$ was defined as symmetry and $180 \pm 60^\circ$ as parallel with anything in between an intermediate mode. Across all IE trials of Figure 2-II the proportion of modes other than the one instructed was 49.61% under parallel instruction and only 17.40% for symmetry, showing significantly higher deviation from the parallel condition (paired t-test, $P < 0.001$). Graphically, this can be understood as the monotonically increasing accumulation of symmetric movement with frequency in biBlindPar and biVisPar, and maintenance of symmetry movement proportional dominance in all other conditions.

No significant differences were found regarding the ability of subjects to coordinate better in the sighted condition over the blind condition when comparing performance within a given frequency band ($p = 0.076$ for DP, $p = 0.110$ for IE). Subjects were able to perform just as well using only proprioceptive information. These results agree with previous literature on bimanual coordination and rhythmic reaching, suggesting that lower limb movements may also be formulated in dimensionally-reduced, perceptive task space variables [39, 40].

Interestingly, symmetric coordination of DP showed significantly greater stability than symmetric coordination of IE ($P < 0.001$). One possible explanation for this is based on the role of IE in bipedal locomotion. During phases of single support, the body can be modeled as a two-dimensional inverted pendulum with the majority of momentum in the sagittal plane so long as stabilizing control effort is applied by subtalar IE muscles to limit rotation in the roll axis [4]. This is a dynamic behavior that requires similarly high control bandwidth, a role better suited for low latency spinal reflexive loops over volitional control. While DP is also understood to be
reflexively activated during the powered plantarflexion portion of gait, there is still considerable volitional control of this motion when navigating terrain and placing footsteps [52]. If the same volitional DP muscle synergies can be applied to the artificial task of rhythmic bilateral coordination, then the difference in performance between these two conditions is accounted for by the hierarchical control of joint function in natural behaviors.

Compared to bimanual coordination figures from Mechsner et al.’s study (Appendix A-1), a greater occurrence of intermediate modes can be observed for all tested IE conditions. If Mechsner et al.’s proposal that coordination is influenced primarily by perception (not necessarily visual) of task space variables holds true, discrepancy in coordination ability can perhaps be further explained by looking at the difference in resources dedicated to lower limb and upper limb sensory perception in the somatosensory cortex. Early electrostimulation studies showed that the hands, fingers, and face generate the vast majority of somatosensory efferent signals while the feet and legs are proportionally underrepresented [53]. Having reduced sensory perception from the lower legs, the mind may be less capable of accurately estimating task space variables in that general workspace.

2.4.2 Volitional AMI Coordination

Validity of Associating AMI Excitations with Intact Kinematics

Subject BKA’s inputs into the GA optimization scheme were chosen carefully to maximize the likelihood of simultaneously capturing intended subtalar motion and AMI excitation with minimal noise. As the first design choice, input data was necessarily limited to a duration of three seconds due to computation time’s generally linearly proportional relationship with simulation length. With an understanding that slow, smooth reaching motions are difficult for humans to achieve [39], the rhythmic bilateral coordination tests were then developed to isolate a frequency of well-behaved motion absent of movement dwell time and to provide an interesting comparison with intact control subjects regarding characteristics of human motor control.
Though relative phase did not reveal significant differences in coordination between sighted and blind conditions in the control group, the blind condition was chosen to allow for comparisons based on proprioceptive control without visual feedback. After analysis of control group relative phase performance in blind IE conditions, all members were found to achieve consistent symmetric coordination at 1.0 and 1.4 Hz, and Subject BKA was observed to be least temporally variable at 1.4 Hz, a fact that is shown in the BKA Blind box plot of Figure 2-13. Thus, a three second window was chosen from the 1.4 Hz band of Subject BKA’s biBlindSym trials where the intact subtalar trajectory was smooth and consistent in movement amplitude.

**Analysis of Optimized Model Output**

The relative phase results of comparing Subject BKA’s optimized IE model output to intact subtalar kinematics shown in Figure 2-10 demonstrate clear agreement with the trends observed in control group bilateral blind conditions. The symmetric condition is more stable \((P < 0.001)\) and both the characteristic monotonic increase of symmetry in the parallel condition and alternatively, maintenance of symmetry dominance are present. However, it can also be seen from the figure that there was greater absolute deviation in Subject BKA’s blind IE performance than in the control group’s, i.e. duller peaks.

Likely explanations for this discrepancy are related to either modeling error or Subject BKA’s fundamental ability to control the AMI. From a holistic systems perspective, both are related through the transfer between neural excitation to model kinematic output and cannot be considered separately. Looking at the model’s outputs in Figure 2-8 first, there is strong phase alignment with the reference trajectory which supports the previously discussed relative phase distribution plots, but also clear overshoot at the inversion peaks. Another distinguishing feature is the notably steeper slope of the model’s position trajectory when rising. Subject BKA’s average velocity profiles in Figure 2-12 visualize this difference as a positive skewness in the model’s average velocity at 1.4 and 2.2 Hz compared to negative skewness measured from the intact side. From the same subfigures, the greater maximum inversion angles
obtained by the model are supported by the differences in total area under the same profiles.

A mechanical understanding of the optimized model is gained from inspecting the final model parameter set of Table 2.3 found from the GA optimization. The TP MTU is around two orders of magnitude stronger ($F_{\text{max}}$) at its optimal fiber length compared to the PL, an inaccuracy when compared to intact physiology. The implications are that even a small amplitude of muscle activation would heavily bias the system toward inversion. The impulse responses for the TP and PL in Figure 2.9 demonstrate this phenomenon. The TP reaches full range of motion with only a 100 ms impulse while the PL barely deviates from the neutral position. From the responses, the model is likely overfit to the input reference trajectory. This is contrasted with the natural out of phase agonist-antagonist activation that would be expected from an intact limb to achieve low frequency oscillatory behavior.

Taking another look at Figure 2-6A, the input AMI excitations themselves demonstrate no increased activity beyond baseline during eversion. Referring back to the bond graph of Figure 2-5, the dynamic model must then provide all of the eversion torque through passive elasticity at the joint or through the parallel elastic element of the PL already mentioned. No other modeled sources of energy are available to explain the behavior. Meanwhile, Figure 2-6B demonstrates that Subject BKA is able to alternately activate her DP AMI to roughly align with measured intact ankle DP kinematics. Knowing that even the intact control group demonstrated great difficulty maintaining consistent relative phase coordination patterns in IE, it is uncertain if Subject BKA displays behavior that supports preservation of volitional characteristics of intact biology or if there is simply a low level of muscle control due to the artificial nature of the AMI construct itself. With only one AMI subject in the case study, it is difficult to definitively isolate contributing factors.

However, it should be noted that even if it is the AMI itself which lacks some degree of native controllability, the optimized model still possessed a sufficiently detailed parameter set to achieve qualitative agreement with control group coordination findings. In other words, proprioception of the AMI is enough to achieve coordination
with an intact subtalar in task space through some NMS model, a central objective of this thesis. Importantly, the human control system does not appear to have significant difficulty symmetrically coordinating two mechanically dissimilar limb systems simultaneously, as evidenced by Figure 2-13. Both the control group’s subtalars and Subject BKA’s intact subtalar show strong inverse correlation of movement amplitude and actual movement frequency in the scatter plots while it cannot be shown that the Subject BKA is more temporally variable than the control group (t-test, $P > 0.05$ for 1.4 Hz to 2.6 Hz) for most tested metronome tempos. Previous literature investigating the human ability to coordinate mechanically distinct ipsilateral limbs supports this finding [43], [54]. Additionally, these bilateral coordination results can be interpreted as evidence of lower limb motion planning in task space variables only, which would agree closely with the simplified perceptual representations of upper limb movement and coordination in task space discussed in Sections 1.4.1 and 1.4.3.

If it can be assumed throughput, as defined in Equation 1.9, is saturated at some sufficiently high movement frequency, then TP can be fixed in value for the range of frequencies beyond that threshold. With fixed TP and decreasing MT, the ratio of $2D$ to $W$ according to Equation 1.8 must also proportionally decrease to reduce ID. Figure 2-14 qualitatively demonstrates this relationship from the data of Figure 2-13, suggesting motion bandwidth limitations in all systems. It should be stated that while the optimized model’s movement amplitudes and actual movement frequencies demonstrate similar human bandwidth limitations compared to both the control group’s and Subject BKA’s intact subtalars as seen in Figure 2-13, the temporal variance shown in the corresponding box plot is significantly different (one-way ANOVA, $P < 0.001$). In followup studies, a more rigorous analysis should be performed with denser data to quantify these relationships.

**Stereotypical Velocity Profiles as a Result of Mechanical Impedance**

With an understanding now of how the optimized model performs relative to Subject BKA’s intact subtalar and to the control group overall, it is worthwhile to discuss potential modeling and optimization improvements that may better capture the char-
acteristics of human lower limb motor control. Based on the following analysis, two potential improvements reveal themselves.

There are many structural similarities between the wrist and ankle-foot. As a brief introduction, studies on wrist movement suggest its dynamics are dominated by impedance in the form of passive stiffness, with passive damping and inertial terms only becoming significant at high velocities \[55\]. In this way, the intact ankle-foot may be considered similar due to its significant ligament structure and musculature compared to the relatively low inertia foot. Stereotypical wrist velocity profiles have also been shown to demonstrate significant skew and are better modeled by \(lgnb\) compared to minimum-jerk which necessitates zero skewness \[56\]. Within the past five years, Michmizos and Krebs \[46\] have found that discrete ankle-foot pointing velocity profiles are likewise skewed and aptly described by the \(lgnb\) function while minimum-jerk trajectories offer a relatively poorer fit, providing evidence that wrist and ankle-foot motions are controlled in an invariant manner. If so, it is also reasonable to propose that the skewed velocity profiles observed in both are a direct result of a dynamical joint system whose impedance is dominated by passive stiffness.

The first potential improvement then involves a reformulation of the model’s dynamic elements. Under the assumption that passive stiffness is necessary for generation of stereotypical skewed velocity profiles, a nonlinear stiffness contribution at the joint may improve resultant kinematic qualities. Ligaments, much like tendons, are described by nonlinear functions of their displacements. An appropriate physiologically inspired stiffness function could replace the simple linear spring to be subsequently optimized over in the GA.

Next, the average intact subtalar velocity profiles in Figure 2-12 and their corresponding calculated metrics summarized in Table 2.4 largely agree with previous literature, even though the rhythmic task is speed-sensitive and fundamentally different from the study by Michmizos and Krebs that did not control for movement duration. All show skewness, platykurtosis, and \(R^2\) values that indicate high agreement with \(lgnb\). Additionally, average peak velocities are seen to decrease at the higher movement frequency of 2.2 Hz, a finding congruent with the decreased move-
ment amplitudes observed from intact subtalars at higher movement frequencies in Figure 2-13. However, the model’s average 2.2 Hz velocity profile is not well-described by lgnb nor does it follow the trend of reduced peak velocity compared to the lower frequency’s average profile.

The second potential improvement involves reformulation of the cost function. The current cost function of Equation 2.6 only accounts for sum of squares error with respect to the reference trajectory, but does not discriminate based on shape of the generated velocity profiles. A weighted cost function incorporating both general reference trajectory tracking and velocity profile fit by lgnb may generate a more physiologically relevant parameter set.

2.4.3 Future Directions

Evidence has been provided suggesting lower limb trajectories are formulated on a high level in task space coordinates, which are dimensionally-reduced compared to intrinsic coordinates. Through optimization of a simplified biomimetic dynamic model, a single subject has successfully demonstrated the ability to simultaneously coordinate one of her AMIs with her intact subtalar in a rhythmic bilateral matching task. Thus, though the AMI is a decidedly artificial biomechanical system, proprioception from the construct appears sufficiently interpretable by the body’s middle layers of neuromuscular control to realize high level trajectories. These early findings suggest the AMI holds promise as a control input for active prostheses.

Immediate questions related to the AMI’s control performance involve comparisons with traditional amputation. A subsequent study between populations of those with AMIs, traditional amputations, and targeted muscle reinnervation [57] would provide researchers a large sum of information on the true nature of proprioception and limb embodiment. If indeed reliable control of task space variables using a single agonist-antagonist muscle pair is sufficient to take advantage of all the compensatory and processing ability of the human controller, the AMI or another more advanced biomechanical construct may have applications beyond control of only active prostheses. Related research may assist the scientific community at large in designing better
paradigms for rehabilitation, teleoperation, and heavy industry.

It also remains to be determined if the AMI naturally preserves walking reflexes and facilitates representation of environmental contact dynamics. A feasible scenario exists where a person with transfemoral amputation controls an active osseointegrated prosthesis through multiple AMIs, all while seamlessly receiving feedback about environmental dynamics via functional electrical stimulation or alternative methods. This can perhaps even be accomplished within just one Ph.D.

If the last 40 years of organismal biomechanics have handled native human biology, then may the next 40 reach beyond.
Appendices
Appendix A

Supplementary Figures
Figure A-1: Bimanual finger adduction and abduction coordination results from Mechsner et al. Reproduced with permission from Springer Nature [40].
Bibliography


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