Enhancing Prosthetic Musculotendinous Proprioception utilizing Multidisciplinary Artificially Intelligent Learning Approach

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Abstract— Historically, research shows analysis, characterization, and classification of complex heterogeneous non-linear systems and interactions have been difficult to accurately understand and effectively model. Advanced Biophysical and Biomechanical prosthesis research shows that development of patient specific physiologically meaningful musculotendinous proprioception would generate a marked impact on reflex control, fine volitional motor control, and overall user experience. Recent advances in Artificial Intelligence are benefitting disciplines struggling with learning from rapid increasing data volume, velocity, and complexity. Research shows complexity reducing axiomatic design benefitting medical devices, but surprisingly not prosthetics. Therefore, we propose a multidisciplinary approach to potentially enhance prosthetic proprioception by combining AI adaptive learning, axiomatic design complexity reduction techniques applied to real-time classification of high volume prosthetic usage characteristics.

Keywords—Prosthetics, Artificial Intelligence, Musculotendinous Proprioception, Complexity, Multidisciplinary

1. Introduction: Non-Linear Systems

Traditionally, much research exists for analysis, characterization and classification of complex heterogeneous non-linear systems and interactions since historically they have been difficult to accurately understand and effectively model [18, 19]. Systems that are nonlinear and dynamic generally comprise combinatorial complexity with changes in variables over time [20]. They may appear chaotic, unpredictable, or counterintuitive when contrasted with much simpler linear systems. Because of complex system interrelationships, chaotic behavior of these systems can sometimes be perceived to be random. However, they are not. Simple changes in one part of a nonlinear system can produce complex effects. Widespread nonlinearity exists in nature [5] Micro- and macroscopic examples include collision-based particles in motion, common electronic distortion, chemical oscillations, the weather, and for this paper Biophysics and Biomechanics as related to neuronal activation. Advanced prosthesis research shows that patient specific physiologically meaningful musculotendinous proprioception would likely incur marked impact on reflex control, fine volitional motor control, trajectory planning, and overall user experience [1, 2]. A multidisciplinary approach is vital to cover the full spectrum of an individual's amputation rehabilitation needs to facilitate successful outcomes [21]. While each discipline is known to have mathematical formalisms which support describing, predicting, and approximating solutions, solution accuracy and analysis are generally problem dependent. For example, for Biomechanics Hodgkin-Huxley (1952) described a mathematical model to explain the problem of nonlinear ionic mechanisms underlying initiation and propagation of action potentials in a squid giant axon which won a 1963 Nobel Prize [6].

Generally, it is also well known that the use of iterative methods, followed by domain specific solution sets, support effective solution generation for nonlinear problems. However, significant difficulty exists in generating most effective proprioceptive prosthetic solutions for inherently multi- trans-disciplinary nonlinear, biophysical, biomechanical, bionic systems. Therefore, we propose, multidisciplinary and transdisciplinary solutions to bridge the combined domain solution sets. Transdisciplinary engineering is the field of study which supports engineering common solutions across many disciplines [17]. Furthermore, recent advances in Artificial Intelligence (AI) and Machine Learning (ML) research is benefitting many disciplines struggling with rapid increasing velocity, volume, and complexity of data and systems for improving timely generation of qualitative readily consumable knowledge [3]. Specifically, we propose, utility of artificially intelligent cognitive system learning methodologies to support continuous biomechanical improvement analogous to human procedural learning, the use of real-time biophysical modeling of volumetric muscle tissue, and ATP activation along with big data processing architectures for optimizing prosthetic space constrained environments [4], complexity theory for reducing and simplifying system complexity, and stochastic diffusion based machine learning process for fine grained efficient distribution of sensing and analysis.

Complexity

Exacerbating the problematic design of nonlinear systems are well known high levels of ambiguity and complexity. Specifically, nonlinear relationships between numerous human physiological and biomechanical systems and subsystems involved in generating smooth kinetic movement, much less the difficult to model brain interfaces involved in proprioception. Although, research and patents exist in the use of visual aids and biofeedback [15] to improve proprioception we propose employment of complexity theory and applications of axiomatic design to enhance management and reduction prosthetic system complexity for ultimately improving prosthetic design and most importantly improved patient usability.

Suh, describes that significant confusion exists within the definition of what is complex. He explains that many attempts to understand complexity in terms of physical entities instead of a focus upon what is to ultimately be achieved. Suh, describes complexity as Computational, Algorithmic, and Probabilistic. Suh's complexity reduction approach comprises four types of complexity: Time-Independent Real/Imaginary Complexity and Time-Dependent Combinatorial/ Periodic Complexity. Suh mitigates overall system complexity by using a few specific set of actions: Reduce the Time-Independent Real Complexity, Eliminate Time-Independent Imaginary Complexity wherever possible, Transform Time-Dependent Combinatorial Complexity into Time-Dependent Periodic Complexity for decomposing complex systems into more robust, optimized, operable units. Suh describes this as determining the Functional Periodicity in whatever domain you are operating within (e.g. Biological, Chemical, Thermal, Circadian, Temporal, and Geometric etc.).

Managing Complexity

Suh, stipulates that complexity must be viewed within the functional domain. Hence, fundamental management of complexity becomes a process of defining what we want to achieve or understand within the functional domain of a discipline, project or need. These pieces of information become the Functional Requirements (FR). How we plan to achieve a goal becomes a set of Design Parameters (DP). Figure 1, describes this concept using a Probability Density Function (PDF). For example, if the prosthetic System Range is completely within the prosthetic Design Range then prosthetic Functional Requirements are more easily achieved, less complex and can produce reduction in time dependent combinatorial non-linearity.

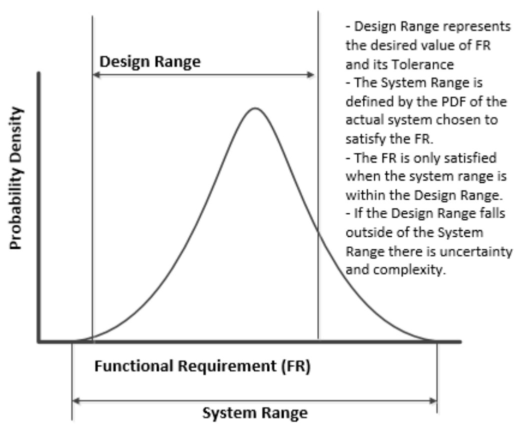

Figure 1, Design vs. System PDF

However, if the System Range extends outside of the Design Range boundaries then the design and the satisfaction of Functional Requirements become more difficult to achieve and therefore is more complex. Axiomatic Design processes are well used in Mechanical Engineering to achieve optimized designs and decomposition into four domains: Customer, Functional, Physical, and Process. Two important axioms govern an optimized design process. The Independence Axiom, maintains independence and orthogonality of functional requirements and supports minimization of design overlap where possible, which drives solutions to minimization and cost effectiveness. Next, the Information Axiom states that minimizing information content throughout the iterative design provides significant simplification. The ultimate objective when employing axiomatic principles is to achieve Uncoupled Designs where all functional requirements are independent and satisfied by independent design parameters and functions.

Analogously, for medical devices and software production, axiomatic design provides a logical decoupling of dependent interfaces and supports development of what is common. Therefore, physical and logical components of prosthetic devices can be abstracted and simplified much more effectively [16]. Thereby, simplifying designs, optimizing prosthesis sensing and management, reducing overall prosthetic system complexity and cost and improved patient usability.

PROSTHETICS

Prosthetic limb control is fundamentally constrained by current amputation procedures. Since the U.S. Civil War, external prostheses have achieved significant innovations, however amputation techniques have not significantly changed [4]. During amputation, nerves are transected without the analysis of proper neural targets, causing painful neuromas and rendering microneurographic activation recordings/feedback infeasible [2,4]. Additionally, physiological agonist-antagonist muscle relationships are severed, making musculotendinous proprioception with a prosthesis very difficult. This feedback is critical for a patient's joint stability, their perceived trajectory planning, and fine motor control [4]. Among other significant innovations within the field of intelligent prostheses, recently, unique prosthetic interface research has improved the fidelity of agonist-antagonist myoneural interface (AMI), unique for surgical implementations used for improving muscle stimulation and prosthesis interaction. AMI functions by regenerating muscle grafts innervated with severed transected nerves and then links them in an agonist-antagonist relationship, in order to attempt to emulate the dynamic interactions normally found within an intact limb [4]. AMI combines biomechanical, electrophysiological, and histological evaluations of the patient, to create efficient viable architecture for generating muscle motor signals bi-directionally [4].

Current prosthetic technology has vastly improved due to the production of new materials and technology, and is now highly adaptable to an individual's residual muscles left after amputation. For lower limb prosthetics, the C-leg is the current state-of-the-art lower limb prosthetic that has a built-in computer to analyze data from multiple sensors and can match the wearer's gait on different terrain [30]. Upper limb prosthetics, however, do not yet possess the same degrees of freedom and dexterity that matches lower limb prosthetics today [31], but significant progress has been made to interface prosthetics with both the efferent and afferent nerve pathways, enabling residual nerves to control machine components and collect sensory data respectively.

Despite these advances, there are many challenges that currently limit the degree of mechanical freedom of prosthetics. Creating a naturally functioning analog of a human arm or leg, taking into account the complexities of human movement and the plethora of materials needed to create the prosthetic, is a truly daunting task. Having prosthetics that maintain the appearance of a normal limb without sacrificing degrees of freedom, withstand normal use for long periods of time, and mimic the flexibility of muscles and tendons, are a few challenges. In the context of our work, we will provide potential improvements for the collection, learning, analysis, and modeling of gait and musculotendinous activation data, from existing limbs, in order to support improvement of prosthetics which can adapt more readily to different terrain, adjust force output, adjust joint angles, maintain proprioception, and regulate and distribute tension, more similarly as a normal limb.

MUSCULOTENDINOUS PROPRIOCEPTION

Proprioception is the body's natural method of relaying information about one's position and strength of effort to the central nervous system (CNS). Musculotendinous proprioception the method of relaying muscle movement to the CNS. It is critical in optimizing an amputee's reflexive, and volitional motor control and trajectory planning [8, 9]. Creating movement of a joint through its range of motion in the absence of a load, muscles act in agonist-antagonist pairs. Contraction and extension cause signals to be sent to the CNS [4]. These signals, in addition to skin and joint sensing receptors, convey limb position information, inform on posture control, joint stability, and enable individuals to more effectively move and interface within their environment [10].

Modeling musculoskeletal health is well researched and significant software modeling tools exist [12, 13]. The study of human movement typically starts from recording of experimental data including whole-body kinematics, foot-ground reaction forces (GRFs) and muscle electromyograms (EMG). Recent research shows that high fidelity biomechanics can be modeled with Electromyography. A framework demonstrated the ability of computing forces in 13 lower-limb muscle-tendon units and resulting moments about three joint DOFs simultaneously in real-time. The significance is that the integration of EMG with numerical modeling will enable simulating realistic neuromuscular strategies in conditions including muscular/orthopedic deficit, which could not be robustly simulated via pure modeling formulations. This will enable translation to clinical settings and development of healthcare technologies including real-time bio-feedback of internal mechanical forces and direct patient-machine interfacing [11]. Hence, proven EMG and other modeling methods provide valuable insights and tools for improving medicine and the human condition. However, because of complexity and the state of the art, like many tools and processes, these methodologies model a macro level of fidelity when considering the vast magnitudes of even smaller biophysical and biomechanical constructs (e.g. cells, mitochondria, proteins, ATP, ions etc.). For example, EMG like EKG and others measure small numbers of feedback locations. Although, we consider the objective of what is "good enough" per our stated problem, we hypothesize herein that finer grained modeling at higher fidelity microscopic levels can provide significant added insights.

2. ARTIFICIALLY INTELLIGENT LEARNING

Many disciplines are generally involved in developing AI systems. Hence, AI research and education is considered inherently Multi- Trans- disciplinary [17], and along with Machine Learning are evolving within domains analogous to Cognitive based learning [22]. Herein, systems may employ computer software utilizing analogous components of the human brain along with varying advances in Artificial Neural Networks (ANN); deemed one of the hallmarks of Machine Learning and designed to operate synonymously as neurons within a human brain, and as a group of interconnected nodal relations. ANN's were inspired by Neuroscience based biological neural networks which are the structure by which chemical based ionic electrical signals are passed throughout the body [23]. They are therefore at the core of the signaling involved in proprioception. Herein, we propose the use of ANN's and cognitive based learning to support the processing of high volume and velocity data and to support automated sensing capture and transfer of real-time bidirectional muscle and prosthetic signaling and messaging. The objective is to potentially improve limb position information transfer, thus improving control of posture, joint stability, and enable individuals to more effectively move and interface within their environment.

LIFE-LONG MACHINE LEARNING

Given that it is beneficial for prosthetic limbs and their usage to improve over time, as they interact with the people that are using them, this requires a different machine learning model than is typically used. Here, we propose analogous continuous, life-long machine learning techniques and algorithms to enable prosthetics to continually improve over time. Standard explicit learning, e.g., deductive and inductive, provide some level of continuous learning, but for the prosthetics to understand what the person means by a given movement takes an abductive approach (hypothesis-based learning). This includes an artificial intelligence system that learns, stores and can recall procedural memories like humans do. Figure 2 illustrates the life-long machine learning process. This is used to describe support for continuous procedural and perceptual learning. Our research shows [24] that there are four types of learning that would be required to fully support a self-learning prosthetic limb.

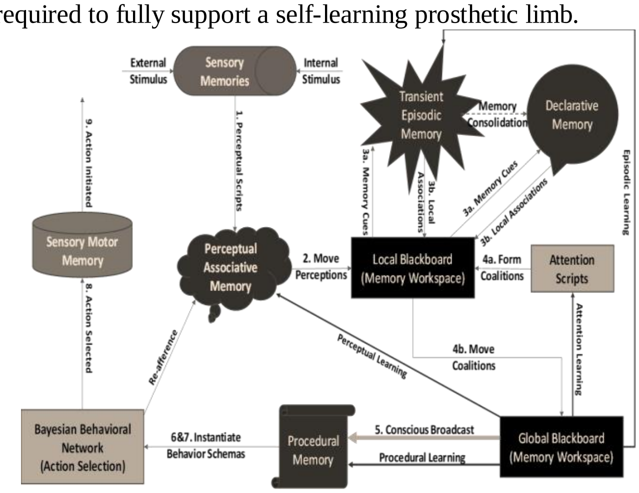

FIGURE 2, LIFE-LONG MACHINE LEARNING PROCESS

1. **Episodic Learning**: the process of storing/ retrieving experiences in the episodic memory and using it to improve behavior (responses to stimulus).

2. **Attention Learning**: also called concentration, attention learning stores triggers that allows the AI system to focus its efforts on objects or events of interest.
3. **Perceptual Learning**: the process of learning skills of perception. This enables continuous improvement in sensory processing (how to distinguish objects from sensory information – (e.g. image object recognition), to complex categorizations of spatial and temporal patterns. Perceptual learning forms the foundation for an AI system to create complex cognitive processes (e.g., language). Perceptual learning drives adaptations (changes) in the AI systems neural circuitry or patterns.
4. **Procedural Learning**: learning by acquiring skill at performing a task. Procedural learning allows the AI system to perform a task "automatically" without consuming resources to determine how to accomplish the task [25].

DATA & DATA VOLUME

Building a viable proprioceptive prosthetic system will require improved individualistic understanding [25]. Our proposed approach utilizes a priori and continuous real-time human subject data and data analysis from soft suit sensors to provide improved subject fidelity and continuous proprioceptive improvements via cognitive learning. A priori data includes individual capture of:

- muscle stiffness,
- muscle tension,
- muscle length,
- joint angles,
- elasticity,
- timestamp event information,
- weight distribution.

This data enables us to analyze and learn benchmark data from the non-amputated limb and compare and contrast that with real-time residual limb muscle interactions. This provides individualized information about the level of each muscle stimulation. Real-time data are captured from sensor feedback and then continuously related back to the previously learned muscle activation, contraction and extension data.

Previous approaches apply histological analysis of the patient and precise modeling of prosthetic sleeve attachment, as well as, bionic and hydraulic actuation [4]. AMI research and approach described earlier had the objective of improving bidirectional signaling for musculotendinous activation and proprioception potential as a surgical procedure. However, as mentioned earlier, research shows that the preponderance of amputees are single limb. Therefore, our solution proposes a non-surgical methodology via the use of prosthetic sleeve attachment described earlier which will sense & capture numerous metrics in real-time from the entirety of the good limb and simultaneously from the sleeve attached to the remaining portion of the amputated limb. The combined learning will be used to in real-time provide feedback that prosthetic manufacturers can use for automated higher fidelity automated actuation responses to the patient. Similar to biofeedback processes this potentially enables more rapid learned proprioception through improved bionic actuation and enhanced human interactive learning.

The overall tasks listed below are used for processing streaming sensor data. Each set of incoming streaming sleeve sensor data is compared, contrasted, associated and normalized against previously captured content to support improved adaptive prosthetic functionality.

- Collect & Verify Data
- Analyze for Missing Data
- Tag Data
- Correlate/Classify with existing Data
- Verify Analytical Results
- Transmit/Display Results

Upon collection from each suit sensor, each input source is decomposed and reduced to its core characteristics utilizing standard Extract, Transform, Load (ETL) solutions which are characterized by the processes listed above. ETL functionality is included for improving scaling of all input source types: (e.g. TCP/UDP Sockets, Filesystems). Recent research of soft sensing suits shows ~16 real-time sensors at a 120 Hz sampling rate [27]. Additionally, we capture soft sensing suit anatomical analysis of 3D marker trajectories to improve fidelity of output to prosthetic devices. As systems and sensors scale up and out we efficiently employ a common ingest and processing Lambda Architecture [14] components, as are included within many high volume data architectures for processing individualized passive/batch and/or active/streaming prosthetic improvement data. Sensor /input data, among others, is transformed as it flows through the scalable ETL process, to ensure it is in the format required for prosthetic analytical algorithms. Once data analytics algorithms have processed the ingest and tagging of the input data, the resulting information must be correlated, combined, and/or fused with any previous results for human adaptive learning and/or subsequently formatted for dissemination to muscle analysis components and prosthetic devices.

3. ANATOMICAL AND PHYSIOLOGICAL MECHANISMS OF MOVEMENT

This section, provides an overview of prosthetic pertinent anatomical and physiological information describing muscle contraction, with objective application to prosthetic improvement which more reasonably mimics natural human movement.

The human body contains billions of neurons, or nerve cells, which are the basic structural units of nerves. Neurons are highly specialized cells that conduct electrical signals, or action potentials, originating from the Central Nervous System (spinal cord and brain) throughout the body, and conduct these signals at speeds approaching 150 m/s. Action potentials travel down the axons of nerve cells and are transferred from cell to cell. In the context of this paper, we focus upon motor neurons that carry action potentials from the central nervous system to muscles and glands. Motor neurons are multipolar and form junctions with effector cells, stimulating muscles to contract or glands to secrete [26].

Thirty-one pairs of spinal nerves, each containing thousands of motor and sensory nerve fibers, extend from various areas of the spinal cord, with each spinal nerve branching into a dorsal ramus and a ventral ramus. The dorsal rami supply the dorsum of the neck and back, and the ventral rami supply the anterior and lateral areas of the neck and trunk, including all regions of the limbs [26]. We focus solely on the ventral rami that innervate, or supply nerves to the muscles of the limbs. Muscles innervated by the rami provide the information measured by external wearable soft sensing materials. The materials can then provide the sensing which is analyzed, learned from, and transmitted to the prosthetic for movement enhancement.

Nerve plexus, (network of nerves), formed by the ventral rami are interconnected networks that occur in the cervical, brachial, lumbar, and sacral regions of the body, with the brachial plexus (Ventral Rami C5-T1) supplying nerves to the muscles of the arms, and the lumbar plexus (Ventral Rami L1-L4) supplying nerves to the muscles of the legs. Nerves from each ventral ramus travel to the periphery of the body via several different routes or branches, and can subsequently diverge into smaller divisions of nerves that innervate different muscles. For example, as part of the brachial plexus, the median nerve innervates a majority of the muscles of the anterior forearm and lateral palm. Branching off from the medial and lateral cords of the C5-T1 ventral rami, the median nerve descends through the arm, lying medial and posterior to the biceps *brachii* muscle, and gives off branches to most of the muscles of the flexor compartment of the forearm and some of the intrinsic muscles in the lateral part of the palm, including the *thenar* muscles used to oppose the thumb [26].

When an action potential propagates from nerve cell to nerve cell and ultimately reaches the muscle cell, it causes functional changes to the contractile unit of skeletal muscle, called the Sarcomere. Sarcomeres consist of thick and thin filaments, which are called myosin and actin respectfully. Through the interaction of myosin, actin, and ATP, the action potential leads to myosin binding to actin, and after ATP is hydrolyzed, causes a "power stroke," in which the myosin head attached to actin pulls the actin filament toward the center of the Sarcomere. This pull action causes a twitch, which is the mechanical response or contraction of an individual contractile unit to a single action potential, and a single action potential will always produce the same amount of force for a given unit in laboratory settings [28]. Summation occurs when a muscle fiber is stimulated repetitively so that the muscle twitch is already in progress when the next action potential arrives, and with increasing frequency of action potential stimulation, the muscles will continue to contract until maximum tension is reached, which is called Tetanus. The amount of force the muscle can generate is proportional to a muscle fiber's cross-sectional area and optimum length, which is the overlap of actin and myosin that allows for maximum interaction. For example, if a Sarcomere is stretched out prior to stimulation, the overlap between myosin and actin is decreased and less tension/force develops as a result. Another variable affecting force production is the steric hindrances created by the muscle filaments when they are contracting and pushed together.

A motor unit, which is comprised of a motor neuron and all the muscle fibers it innervates, can vary by the number of muscle fibers contained within that unit and by the diameter of the muscle fibers. Stimulating additional motor units in a muscle can also increase the strength of a muscle contraction, which is called recruitment. In other words, stimulating or recruiting more motor units leads to the creation of more force. Motor units with small numbers of muscle fibers allow for finer control in regards to the tension created, with smaller motor units controlling things such as eye movement and larger motor units controlling things such as maintaining posture. Motor units containing small fibers are typically recruited first due to the lower frequency of action potentials needed to reach Tetanus, and large motor units are recruited last. In regards to this, small fibers tend to be innervated by smaller diameter nerves and large fibers by larger diameter nerves, with the diameter of a motor nerve being proportional to the diameter of the muscle fiber it innervates.

There are also various degrees of stimulation for the recruitment of motor units. A submaximal load is a mechanical exercise where not all motor units are utilized, and a maximal load is a mechanical exercise where all motor units are utilized. For a submaximal load, the motor units of the particular muscle are not activated at the same time but are recruited asynchronously. This asynchronous recruitment enables motor units to essentially 'take turns' maintaining muscle tension and help avoid lactic acid build-up, depletion of energy reserves, and neuromuscular fatigue during sustained Tetanus. In addition, there are also elastic components, such as tendons and ligaments, which contribute to musculoskeletal stability by transmitting force generated by contractile elements to the skeletal components to which they are attached. In isometric contractions, tension is created in the muscle, but does not have enough force to overcome a mechanical load, therefore the muscle cannot contract, and the elastic elements lengthen. In isotonic contractions, tension is generated which is at least equal to the force opposing it, meaning that the sarcomeres contract and the elastic elements lengthen in response.

These interactions between nerves, muscles, and muscle groups form the basis for proprioception and fine motor control for the creation of natural movement.

Measuring Biomechanical data and Translation to Prosthetic Creation

Various methods for measuring biomechanical data exist, and the comprehensive modeling of data pertaining to human gait or arm movement is important to understanding the interactions between muscles in motion, and important for the creation of prosthetics that are individualized for each person. We will be operating under the assumption that prosthetics can be built to match the size, weight, and dimensions of the limb that was amputated. In addition, amputation statistics and trends shows that there is a much larger magnitude of single-limb amputees compared to double-limb amputees, and the theories presented will reflect methods that utilize the opposing non-amputated limb to gather data, in order to improve the activation fidelity and ease of movement of the prosthetic limb.

One such method is a wearable soft-sensing suit used in the measurement of human gait, with wearable robotic sensors that more intimately interface to the wearer than rigid exoskeletons, allowing wearers to maintain natural movement patterns [27]. This will provide the ability to non-invasively monitor the motion of impaired and healthy individuals in unrestricted settings. The visual tracking elements of the suit provide accurate and precise measurements in regards to human motion analysis, with passive retroreflective or active markers placed at key bony landmarks, and errors around just 1mm [29]. However, the drawbacks of visual tracking information include the inability to detect rotated joints or overlapped body parts, thereby preventing the use of 3-D rendering, and require significant post-processing and kinematic model development [27, 29].

At each point of natural movement, with muscles receiving varying amounts of stimulation, sensors can be modified to measure characteristics such as muscle tension, stiffness, muscle length changes, weight distribution, joint angles, and elasticity, among others. In utilizing machine-learning concepts and pattern-recognition software, this information can be used to measure muscle interactions and be extrapolated to prosthetic dimensions, individualizing prosthetics so that they directly emulate an individual's normal limb and learn normal movement over time, thereby eliminating the need for amputees to wear multiple prosthetic devices for different activities. For additional and supplemental information gathering, the soft-sensing suit can be applied to the amputated limb and provide data for the capabilities of the muscles that remain active, and can also be applied to the non-amputated limb to constantly record information over a period of time, which relays information to an adaptive-learning prosthetic to improve activation fidelity.

4. Conclusions and Discussion

This is preliminary work and significant research is still required. Here we have presented a cognitive adaptive learning architecture, axiomatic design complexity reduction techniques applied to real-time classification of high volume prosthetic usage characteristics and high fidelity muscle modeling. Together, these capabilities potentially produce more efficient bionic actuation and high fidelity data from real-time gait analysis. This potentially improves kinetic gait information (e.g. muscle stiffness change, hysteresis, linearity, strain %, high fidelity muscle locality, joint angles and max. extension) to more properly assess degrees of freedom needed for prosthetic manufacturers. Thereby, providing increased prosthetic controllability and sensation, while also minimizing nonlinearity and maximizing usability. Suggested next steps are to complete the architecture, derive requirements and prototype the system. Future papers will present progress and results as available.

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