Motivation

Animals do not struggle with many of the navigational challenges that trouble robots, suggesting that a biologically-inspired control system could be an effective foundation for robotic control. Understanding the exact mechanisms that animals use to coordinate hierarchical sensorimotor pathways requires invasive experimentation that can impede the natural performance of the system. Biomechanical models have been developed to better understand the complex interplay of the nervous and body systems. Sufficiently sophisticated biomechanical modeling tools must be created to address the wealth of biological data as it increases with further experimentation. This work discusses the development of a biomechanical model through the lens of simulation tools which could aid in future model development.

The growing inclusion of biomechanics in robotic design emphasizes the importance of incorporating principles of “living machines” into product development. Roboticists are beginning to incorporate musculature in these robots and even integrating biological control systems to coordinate them (Sharbafi et al. 2016; Luo et al. 2018). Studies have been done on many types of locomotion such as swimming (Weeks and Jr 1978), flying (Chung and Dorothy 2010), or undulating (Bryden and Cohen 2008). Robots inspired by insects have exploited the inherent stability of alternating tripod gaits (Beer et al. 1997; Szczecinski, Brown, et al. 2014, Szczecinski, Martin, et al. 2014). Rat locomotion has been studied extensively and replicated in simulation (Morrison 1970; Witte et al. 2002; Fischer et al. 2002; Andrada et al. 2013). Legged locomotion is a preferable modality for environments navigated by humans but its complexity necessitates sophisticated processing methods and robust actuators.

Modeling considerations

Quality biomechanical models can provide insight into how animals “work” but effective models must consider all relevant systems for insight into adaptive behavior. Three broad systems interplay to determine an animal’s emergent behavior: the environment in which the animal exists, the body that the animal uses to manipulate itself or the environment, and the nervous system that the animal uses to control the body. Complex feedback mechanisms between these layers exist, with the nervous system controlling the body using neural “suggestions” rather than “demands”, issuing generalized commands that are contingent on the states of the body and environment (Chiel and Beer 1997). The simultaneous development of feedback mechanisms between these interconnected systems are lost when considering any system in isolation (Chiel et al. 2009). Developing biomechanical models that accurately emulate emergent behavior resulting from the intertwined nervous and body systems is contingent on simulating their interaction with environmental factors as realistically as possible.

Understanding the activity of the nervous system is a complex process due to its highly nonlinear relationship with the body and environment. Recently, a novel neural design approach has been developed that compartmentalizes groups of neurons into algebraic subunits, called functional subnetworks (FSN) (Szczecinski, Hunt, and Quinn 2017a). Networks designed using the FSN approach include known functional relationships when morphological components are not fully understood. Decomposing larger systems into modular components allows for iterative network development as new biological structures are studied. FSN design has been used to control locomotion in robots modeled after a dog (Hunt, Szczecinski, and Quinn 2017; Szczecinski, Hunt, and Quinn 2017b) and a praying mantis (Szczecinski, Martin, et al. 2014).

One tool used to develop biomechanical models is Animatlab, a simulation program that includes both a physics engine and a neural design environment (Cofer et al. 2010). Animatlab allows researchers to simultaneously design organs and the neurons that innervate them. This tool is an asset for testing neural configurations and rapidly prototyping novel control schemes based on new discoveries. The use of this program, chiefly as it relates to modeling the layers of emergent behavior, will be discussed as it relates to a model of rat locomotion.

**A Walking Rat Model: Previous Project Developments**

This work discusses advancements made to a model developed by Dr. Alexander Hunt in completion of a doctoral thesis (Hunt et al. 2014; 2015; Hunt 2016). In Hunt's work, an artificial neural network coordinated hindlimb muscle contractions on an articulated biomechanical rat model in a simulated environment. Joints were controlled by discrete subunits known as central pattern generators (CPGs), bilateral neural subnetworks which oscillate in the presence of a constant input. CPGs have been used extensively in models that control locomotion (Beer, Chiel, and Gallagher 1999; Ijspeert 2008; Chung and Dorothy 2010; S. O. Schrade et al. 2017; Duysens and Forner-Cordero 2019; Dutta et al. 2019). Hunt’s model is a useful example of the multi-layer modeling that is crucial to understanding emergent behavior. However, the modeling practices used to coordinate its locomotion rely on a number of simplifications that must be addressed in order to design a model that falls more in line with a living animal.

Hunt’s model incorporated a hierarchical CPG system inspired by work from McCrae and Rybak’s work in a cat model to coordinate joint motion (McCrea and Rybak 2008). Neural control of locomotion is abstracted into hierarchical layers composed of CPGs with a high order rhythm generator (RG) layer and a low level pattern formation (PF) layer. Hunt’s model has a discrete PF unit at each joint, oscillating between flexion and extension. This simplification is useful because it allows for a one-to-one connection between the CPG half centers (bilateral neurons with alternating activation) but lacks a distribution method for accommodating the inclusion of more muscles.

An animal’s ability to generate propulsive and stabilizing limb forces is dependent on a complex interplay of muscle lines of action across multiple joints. Hunt’s model excludes muscles which span multiple joints, known as biarticular muscles (Cleland 1867). While monoarticular muscles primarily generate forces along the length of a bone segment, biarticular muscles are critical for generating transverse forces (Hof 2001). Utilizing the multi-level CPG hierarchy of McCrae and Rybak, a one-to-one connection between half-center neurons in the CPG and antagonistic muscles was possible. The inclusion of biarticular muscles introduces a design challenge when considering how a discrete, joint based control system can be generalized to coordinate contractions of muscles whose activity is not exclusive to a single joint. Work has already begun to address this design challenge through neural control but has not yet integrated a complete muscle set (Deng et al. 2019).

**Methods for Neural Modeling: Synergies**

Organizing muscles into groups whose contractions have temporal and spatial correlations, referred to as “muscle synergies”, is a biologically representative method of improving the computational efficiency of a control system (W. A. Lee 1984; Tresch, Saltiel, and Bizzi 1999). Implementing a synergy-based neural control system could accelerate optimization techniques necessary for the implementation of the FSN method by reducing the dimensionality of the parameter space that the nervous system must control (Ting and Macpherson 2005; Aoi et al. 2013; Alessandro, Carbajal, and d’Avella 2014). Muscle synergy analysis has broad uses including viability in clinical, robotic, and sport analysis (Taborri, Agostini, et al. 2018; Steele, Rozumalski, and Schwartz 2015).

Statistical methods are used to identify muscle synergies by decomposing electromyography (EMG) measurements from many muscles while completing a task. Multiple matrix factorization techniques have been used to characterize synergy profiles (Andrea d’Avella, Saltiel, and Bizzi 2003; Tresch, Cheung, and d’Avella 2006; Torres-Oviedo and Ting 2007; Taborri, Palermo, et al. 2018), with the most common being nonnegative matrix factorization (NNMF) (Ting et al. 2012; D. D. Lee and Seung 2001). In NNMF, rectified, low-pass filtered EMG recordings are decomposed into a set of spatial vectors, representing time invariant muscle activation profiles, and temporal vectors, representing the timing of synergy coactivation. The overall muscle activation characterizes the relative activation of muscles in the hindlimb at a point in time and determines the kinetics that the leg produces.

The synergy model has recently come under scrutiny as researchers have posited that synergies are less likely manifestations of physical neural systems and moreso optimal task-specific responses from the body (Perreault et al. 2008; Tresch and Jarc 2009; Kutch and Valero-Cuevas 2011). The task-specific focus of muscle synergy derivation does not mean that the model is unsuitable for robotic control, though, so long as the natural dynamics of the systems are considered within the task demands (A. d’Avella and Bizzi 2005; Berniker et al. 2009).

**Perturbations**

Nominal walking patterns are kinematic profiles (joint angles, torque patterns, muscle activation, etc.) that describe limb motion during unimpeded flat ground walking at a self-selected speed. The development of nominal models are useful because they are relatively easy to create and there is a wealth of nominal metrics available in the literature. Ultimately, nominal patterns reveal little about the dynamic interplay between the nervous system, body, and environment because they fail to activate afferent feedback pathways that respond to environmental uncertainty. Adding perturbations to kinematic responses, such as obstacles to jump over or holes to fall into, trigger different actions. Analyzing these reflexes, as they manifest in joint kinematics and muscle EMG patterns, can suggest new pathways in the hierarchical structure of walking systems.

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Modeling Considerations

An effective control system should accommodate environmental uncertainty by coordinating responses at appropriate timescales and processing sensory feedback based on the complexity of the necessary response. A complete biological map of a living system’s feedforward and feedback systems would demonstrate how its internal structure meets the demands of the task-environment space. Unfortunately, the biological experimentation necessary to create such a map is often impossible to attain. As such, it is necessary to model neuromechanical systems so as to avoid impeding the natural activity of a system and to distill this wealth of biological information into a form that is useable for control of robotic systems.

Modeling living systems is an iterative process that oscillates between searching for new structures, modeling the structures, testing the response of known structures, and replicating them in simulation. There are different approaches to modeling depending on experimental goals. Often, modeling assumes a morphological or functional approach, depending on whether the model is focused more on engineering or biology (Buschmann et al. 2015). In a morphological approach, the biological components of the control system have direct representation in the model. This is often appropriate for systems that have well-documented biological systems with high specificity, making it possible to represent the system as specific neurons or neuron groups. Functional approaches prioritize replicating output metrics (e.g. joint motion, output torque) rather than direct biological representation. Functional approaches are more common in robotic applications where designs are constrained by manufacturing limitations. Morphological approaches are more common in biological studies because they allow researchers to experiment with systems that may be impossible to test in a real environment.

My proposed model takes a morphological approach while maintaining emphasis on the functional demands of a robotic control system. Specific neural systems from cats and have been implemented in the model. Functional data from Fischer has been included as an output metric for testing the modeled physical system.

Rats as a Model

Previous Project Developments

Synergies

Perturbations