ABSTRACT
The neuromuscular systems of animals are governed by extremely complex networks of control signals, sensory feedback loops, and mechanical interactions. Morphology and control are inherently intertwined. In the case of animal joints, groups of muscles work together to provide power and stability to move limbs in a coordinated manner. In contrast, many robot controllers handle both high-level planning and low-level control of individual joints. In this paper, we propose a joint-level control method, called digital muscles, that operates in a manner analogous to biological muscles, yet is abstract enough to apply to conventional robotic joints. An individual joint is controlled by multiple muscle nodes, each of which responds to a control signal according to a node-specific activation function. Evolving the physical orientation of muscle nodes and their respective activation functions enables relatively complex and coordinated gaits to be realized with simple high-level control. Even using a sinusoid as the high-level control signal, we demonstrate the evolution of effective gaits for a simulated quadruped. The proposed model realizes a control strategy for governing the behavior of individual joints, and can be coupled with a high-level controller that focuses on decision making and planning.

Categories and Subject Descriptors
I.2.9 [Computing Methodologies]: Artificial Intelligence—Robotics, Autonomous vehicles

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Evolutionary robotics, digital muscles, joint-level control, simulation, bio-inspired design

1. INTRODUCTION

Biological organisms demonstrate a remarkable level of complexity in both their bodies and brains. Together, morphology and control coordinate movements among multiple joints [6,8], each of which is governed by groups of muscles. Multiple muscles work together to express different behaviors, from simple locomotion to fine motor skills [7,12]. In contrast, robotic joints are often implemented using single degree of freedom (DOF) actuators, manipulated by robotic controllers that are relatively decoupled from the underlying robot morphology. Our work explores the integration and co-evolution of joint-level control and joint morphology, which together respond to high-level control signals in order to produce movements.

In this paper, we propose a digital muscle model that emulates the function of biological muscles, yet is abstract enough to apply to engineered systems and biological study. Receiving commands from a high-level controller, muscle groups define the movement repertoire of individual joints. The model integrates aspects of both morphology and control, which are evolved together. By delegating joint-level control to muscle groups, a high-level controller is free to address complex tasks and decision making.

The digital muscle model helps to bridge the gap between control and morphology. Instead of being explicitly encoded in the genome, aspects such as joint ranges emerge from the interaction between components of the model and the environment. Here, we apply the digital muscle model to the evolution of locomotion in quadruped animats. Evolved agents demonstrate effective gaits that exhibit symmetry and coordination among individual joints, even though they are driven by a single, shared sinusoidal control signal. We emphasize that this model is not intended to replicate the functionality of physical muscles, but rather to provide an abstraction of joint-level control that can be mapped into robotic systems or used to help understand the evolution of natural organisms.

The remainder of this paper is organized as follows. Background and related work are presented in Section 2. The proposed digital muscle model is described in Section 3. Experiments are detailed in Sections 4 and 5 with results following in Section 6. Possible applications of the model are presented in Section 7, while Section 8 offers conclusions and discusses future work.
ment of natural organisms is a complex interaction between an individual’s neuromuscular and musculoskeletal systems.

In nature, morphology and control evolve together to produce effective behaviors. In the case of a robot, the inclusion of morphology in the evolutionary process can greatly increase the robustness of an individual [2]. The embodiment of a controller within a morphology [26] allows for a high degree of integration between the two. Bongard and Paul [25] demonstrated the importance of co-evolving control and morphology in a biped robot platform; small changes to the robot’s mass distribution had large effects on the resultant gait. Other studies have shown success in modular self-organizing systems [17] and the development of locomotion strategies for robots with different morphologies [1]. Doncieux and Meyer [9] have shown that it may be difficult, if not impossible, to develop complex control strategies without structural modularity in neural networks. In the proposed digital muscle model, we focus on evolving parameters that affect aspects of both joint control and joint morphology. Whether modularity associated with joint-level control adds further benefits remains an open question.

Lessin et al. [15] developed models of physical muscles that connect rigid bodies, with movement determined by a variable spring constant. Actuation occurs when the constant is changed, resulting in contraction or expansion of the simulated muscle. In these virtual creatures, the evolution of multiple behaviors was investigated, with natural looking movements provided by the muscle-based effectors. Geijtenbeek et al. [11] demonstrated virtual bipeds, controlled by simulated muscles, capable of walking on both flat and varying surfaces. Muscles are simulated with physical properties governing attachment points, contraction paths and actuation parameters that are determined through optimization. Gaits are effective in different morphologies, demonstrating realistic movements for the virtual creatures. While promising, these systems emulate physical muscles directly, which may complicate their mapping onto actual robotic systems.

Consequently, at least two nodes, aligned as an antagonistic pair, are necessary to have both flexion and extension in a joint. Of natural muscles, which are only capable of active contraction.

3. DIGITAL MUSCLE MODEL

Biological muscles provide the power necessary for organisms to move and interact with their environment [8]. Working in antagonistic pairs, muscles allow for flexion and extension of individual joints, coordinated by neural systems [6,7]. Although in some cases movement may appear to occur within a single DOF (for example, a knee extending), multiple muscles work together to both move and stabilize a joint. The proposed digital muscle model provides an abstract control layer that emulates the fundamental properties of biological muscles, while still being suitable for realization in terms of conventional robotic actuators. Aspects of both control and morphology are integrated in the model, allowing for both to be evolved simultaneously.

Figure 1 depicts a simple example of the digital muscle model. Movement of the lower segment is controlled by four muscle nodes, whose locations and activation functions are evolved. All nodes in a muscle group receive the same signal from a controller (in this paper a simple sinusoid), with the activation function of each individual node determining its behavior. The combined responses of the muscle nodes along with their evolved positions determine the behavior of the joint. In Figure 1 the muscle nodes are equally spaced around the joint, but in general these locations are evolved.

![Figure 1: A digital muscle group controls one joint in an animat](Image 360x564 to 483x738)

**Control.**

The activation function of a digital muscle node governs when and how strongly it contracts, that is, pulls on a limb segment. This pulling force determines how far and fast a limb segment moves toward the node’s position relative to the joint. Activation functions can be any function that maps an input signal to a corresponding output value. For this study, activation functions are Gaussians with evolvable parameters: $\mu$ (center), $\sigma$ (spread) and $\alpha$ (magnitude). Nodes are limited to positive exertion values, similar to the function of natural muscles, which are only capable of active contraction. Consequently, at least two nodes, aligned as an antagonistic pair, are necessary to have both flexion and extension in a joint.

**Morphology.**

Figure 2 shows the spatial component of muscle nodes, namely, where they are located with respect to their associated joint. Each node has an evolvable parameter that defines its position on a unit circle around the joint. This position determines which direction the limb will be pulled when a node contracts. Relative positions of muscle nodes evolve over generations. The result may be a joint with a wide range of motion, as in a human shoulder, or one with limitations, as in a knee joint.

**Motor Control Signal Generation.**

The activation functions of the nodes in a muscle group collectively define the response of the joint to an input signal. Activation functions for a sample group with 4 nodes can be seen in Figure 3. In the figure, an input signal value of -0.5 results in nodes 0, 1, and 2 exerting themselves with activations of 0.77, 0.42, and 0.28, respectively. For example, if the nodes were aligned as shown in Figure 2, then movement of the limb would be away from node 3, which does not contract at inputs under -0.1.

Joint behavior is calculated by combining the activation outputs from all nodes in a group for a given input value. The outputs for
than unique signals for each muscle node. A high-level control signal which is distributed to the nodes. A high-level input signal determines the response of nodes according to the activation output and (x,y) coordinate of each node. Together, these determine the strength and direction of pull placed on a joint by the individual node.

Each node has both an activation function and a spatial component. The response is an emergent property of the model, rather than directly dependent upon the specific activation function or single evolved parameter. Joint movement speeds are calculated as the difference between current and desired joint positions for the next time step. The speed of movement may be included as an output in the model in future experiments. Each node is projected into two values, one for each axis of the 2-DOF joint, according to the activation output and (x,y) coordinate of each node in a group. Figure 4 shows the results of aggregating the muscle node activations plotted in Figure 3. In this manner, both the activation function of each node and its spatial location contribute to the response of the joint. The response is an emergent property of the model, rather than directly dependent upon the specific activation function or single evolved parameter. Joint movement speeds are calculated as the difference between current and desired joint positions for the next time step. (The speed of movement may be included as an output in the model in future extensions.)

Figure 3 shows the mapping of a high-level control signal (in this case a simple sinusoidal wave) to the response of a hip joint in a quadruped. A muscle group, composed of multiple nodes, is mapped to a single joint in an animat. Each muscle group receives a single control signal which is distributed to the nodes. A high-level controller then needs only to provide one signal per joint, rather than unique signals for each muscle node.

4. EXPERIMENTS

We conducted experiments in evolving walking gaits for the quadruped animat shown in Figure 5f. This animat has two 2-DOF joints per leg. Evaluations were conducted using the Open Dynamics Engine (ODE), a 3D physics simulation environment [29]. ODE simulates forces such as gravity and friction while providing a collision engine for the robot. In the proposed model, 2-DOF joints allow the connected limb to move anywhere in 3D space, within the physical constraints of the animat. This approach also allows for fabricating evolved individuals in a physical robot using two servo motors, rotated 90 degrees to each other.

Treatment 1 - Digital Muscle Model.

Treatment 1 features individuals whose high-level control signal is a sinusoid. A population of 100 individuals evolves for 12,000 generations, using a conventional genetic algorithm, with both crossover and mutation applied at each generation. For each treatment, we execute 20 replicate runs, each initialized with a unique starting seed. Individuals contain 8 muscle groups, in which the positions of nodes are initially evenly distributed around the joint with randomized parameters for the nodes. During a simulation controllers are activated every 20 milliseconds. Fitness is the Euclidean distance from the starting location after 5 seconds of simulation time. The next generation is populated using 2-way tournament selection. Elitism is not used in this study. Crossover and mutation are applied with 10% and 2.5% probabilities, respectively. For purposes of crossover, individuals are treated as a composition of muscle groups. During the operation, a child individual is created from two parents, with muscle groups assigned to the corresponding joints. Genomes in this treatment consist of 128 parameters (8 muscle groups * 4 nodes * (3 gaussian + 1 position parameter)), resulting in an average of 3 mutations per genome. Individual parameters are mutated using a normal distribution around the current value with an approximate range of ±10% of the parameter value.

Treatment 2 - ANN Controller.

In the second treatment, individuals are controlled by ANNs evolved with the NEAT algorithm [30]. We emphasize that the proposed digital muscle model is not intended to compete with ANNs, but rather to complement ANNs and other high-level controllers.
Evolution of Symmetric Movements.

We observed the evolution of symmetric behavior among joints in the gait depicted in Figure 6a. In this gait, the rear legs provide forward propulsion, moving symmetrically, with the front acting to keep the body upright. A video showing snapshots during the evolution of this gait can be seen at the following address: http://youtu.be/42w3WW59l6w. The evolution of multiple different gaits across the replicates demonstrates the expressive capacity of the muscle model for a given morphology. The emergence of relatively complex gaits suggests that individual muscle groups evolve to coordinate with each other. As a whole, behaviors tend to balance speed (fore/aft movement of the limbs) with stability (splaying limbs outwards from the body).

Evolution of a Functional Knee.

Although joints in the animat have 2 DOF, the muscle model allows for functional specialization to 1 DOF joints. For example, in one of the replicates, the second joint of the rear left leg evolved to a functional knee joint. Figure 11 shows the evolution of this joint-level control, while a video can be seen at the following address: http://youtu.be/Q7LwNMfD1g. In the first few generations, the joint flexes in response to the movement of other joints in the animat, as opposed to providing direct thrust for movement. This behavior serves to keep the animat stable while the other limbs provide thrust for movement. In later generations, however, the joint assumes an active role, as different muscle groups start exhibiting coordination across the animat. The expressed behavior in the muscle group evolves to an ellipsoid, elongating and narrowing. By generation 300, most of the reactive and jerky movements observed in earlier generations disappear. Planar movement and interaction between multiple muscle groups required to express effective gaits. Evolution of symmetric movement is apparent in Figure 8, wherein, movement away from the body is initially quite different between the hips. Over the course of evolution, these two muscle groups exhibit like behaviors, ultimately demonstrating similar phase, period, and amplitudes. Coordination in both axes of movement of the hips results in an effective forward bounding gait.

Figure 9 shows the movement paths for the rear hips at different points during evolution. Here, the early generation individual exhibits a shuffling gait where the right rear hip pulls the leg under the robot. Early generation individuals also exhibit random movement trajectories, with little observable coordination between the two axes of movement. This is illustrated by the erratic paths for both joints. Over the course of evolution, however, these movements smooth out, ultimately producing roughly ellipsoidal trajectories. In addition to the smooth movements within a joint group, the evolution of left/right symmetry can also be seen between the two hip joints.

Figure 10 shows the evolved configuration of the muscle nodes for both muscle groups in the rear hips. Here, three of the four nodes in each muscle group are relatively similar in spatial position. Even though the fourth nodes are not close to each other, the expressed behaviors, as indicated by the previously discussed figures, are quite similar. In the muscle model, similar behaviors can emerge, despite completely different muscle node configurations, as both activation and spatial positioning determine the contraction of each node.
Figure 6: Examples of evolved in digital muscle based animats. (a) Rear leg driven bounding gait with left/right symmetric motion. (b) Three legged pace gait, where the left legs move in unison, out of phase with the right rear leg. (c) A three legged bounding gait with both left and the right rear leg moving in near unison.

Figure 7: Evolution of forward and backward movement of the rear hips in a bounding individual. Positive angles indicate forward movement. Initially, the joint movements are not synchronized and differ in amplitude. As evolution progresses, the movement of the hips becomes synchronized, with the joint angles moving toward a common phase, amplitude and period. Knee-like functionality are observable by generation 1,000, with this behavior becoming more refined in the final individual at generation 11,999.

ANN Evolved Controllers.

Evolved gaits with ANN controllers were also found to be effective, although the individuals tended to remain low to the ground, apparently to maintain stability. Figure 12 shows a representative gait evolved using NEAT. Many ANN-based controllers exhibited similar movement among all legs, rather than anti-phase movements, as in walking or pace gaits. This pattern emerged in the majority of the replicates. This behavior led to lower fitness than the gaits evolved in Treatment 1. The synchronous movement is likely due to the evolutionary method of complexification in NEAT, which results in the growth of networks from an initially fully connected state. In addition, the lack of environmental inputs forces the ANN to work with only a single stimulus. As a result, multiple legs receive the same or similar control signals from the ANN.

Performance Comparison.

Figure 13 plots the evolutionary trajectories and fitness performance for the two treatments. In this study, evolved muscle model controllers outperform ANN controllers, with the maximum and average fitnesses being significantly different ($p < 0.001$ t-test). Quantifying the behaviors across treatments is difficult due to the variety of gaits that evolve. However, one indicator of general behavior is the average height above the ground for the main body of the animat, plotted in Figure 14. Individuals with a muscle model controller tend to maintain higher main body positions than those with ANN controllers. Higher postures are indicative of walking, as opposed to a low crawl or shuffling gait. Observations of the sample gaits from each treatment support this interpretation, the individuals from Treatment 1 exhibit more vertical leg standing postures, whereas ANN based controllers limbs are splayed outward,
with the main body often contacting the ground. Although it provides stability, such contact results in drag, reducing velocity. Individuals that avoid this behavior, as is often the case in Treatment 1, are able to move more effectively, resulting in higher fitness values.

6. POSSIBLE APPLICATIONS
As noted earlier, although the digital muscle model presented in this paper is compared to an ANN based control strategy, the two are not meant to be competitive. Instead, the muscle model is intended to provide a means to co-evolve joint-level control and joint morphology. High-level control strategies can be governed by an ANN or rule-based control strategy. The muscle model may then produce basic gaits without requiring much input from a higher level controller, freeing those resources to be applied to more complex maneuvers and decision making. Gaits evolved in Treatment 1 are driven using only a sinusoid control signal, in order to help us understand how the muscle model functions under controlled conditions. In future work, we plan to investigate multi-tiered control strategies.

In addition to serving as a robotic control strategy, information about evolved orientations of muscle nodes and activation functions can inform biology. Given the incomplete fossil record, evolutionary algorithms and simulation provide a means to test different hypotheses regarding joint-level control and its role in locomotion. Understanding the mechanics of specific motions and muscle configurations is of interest to the study of biological organisms [19, 22, 23]. Evolutionary experiments can yield insight into the biomechanics underlying basic movements [20]. However, finely detailed musculoskeletal simulations are impractical for use in computational evolution. In such musculoskeletal simulators, single experiments require multiple days of computation time for a single analysis, with the process often requiring multiple iterations. Moreover, while these simulations provide insight into the neuromuscular control of living animals, they are limited in their ability to explore alternative morphologies or behaviors. The digital muscle model presented in this paper provides a way to simulate the basic mechanics underlying natural muscles without the high overhead cost of more detailed simulations. Individual runs (1.2 million evaluations) conducted for this study took approximately 24 hours using a server with 24 cores. Information obtained from this model can then be used as a basis for creating models in more detailed simulators, shortening the iterative cycle.

7. CONCLUSIONS
The digital muscle model presented in this paper is meant to provide a bridge between aspects of control and morphology at the joint level. Each muscle group provides a low-level control strategy that defines the behavior of an individual joint. In contrast to a comprehensive control strategy that supports high-level cognitive tasks (waypoint following, path planning), mid-level (walking, turning), and low-level (basic movements, extension, flexion), the muscle model is intended to function as a low-level controller only. Additionally, the proposed model serves as a computationally efficient tool to assist biological study when using computational evolution. These features, along with the abstract nature of the control strategy, allow the digital muscle model to map into robotic systems while also informing biological study. Results show that effective gaits can evolve using the digital muscle model with instances of functional specialization, coordination, and symmetry all appearing in evolved individuals. Future work will involve exploring more robust behaviors and integration with ANN-based high-level controllers.

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Figure 11: Joint movement for the left rear knee over evolutionary time. The joint initially moves somewhat erratically, in both degrees of freedom with a noticeable hitch. At generation 50, the joint has a balanced movement between both axes but still has jitter. This results in jerky movement of the lower limb. As evolution progresses, the movement becomes planar, using a combination of both degrees of freedom. A functional knee joint then arises with the lower limb moving steadily back and forth without much side-to-side movement.

Figure 12: Evolved three legged bounding gait using an ANN-based controller. The main body remains low to the ground throughout the evaluation period, emphasizing stable locomotion. Limbs exhibit symmetric movements, likely due to the complexification of the ANN over evolutionary time.

Figure 13: Evolutionary fitness progressions for both treatments. Shaded areas indicate the 95% confidence intervals across 20 replicate runs per treatment. Both the maximum fitness distribution and average fitness distribution are significantly different (p < 0.001 t-test).

Figure 14: The average body height above the ground for all replicate runs between the two treatments. Shaded areas indicate 95% confidence intervals with the two distributions being significantly different (p < 0.001 t-test). As a whole, gaits from digital muscle model controllers evolve higher postures as legs are typically held closer to vertical. Whereas, ANN controllers evolve gaits that tend to remain closer to the ground, splaying the legs outward.

8. REFERENCES


