Applying Evolutionary Computation to Harness Passive Material Properties in Robots

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ABSTRACT

Evolution has produced a wide variety of organisms that interact with their physical environment through musculoskeletal systems. Movements are often aided by passive characteristics of an organism's body and the inherent flexibility of muscles. Emulating these characteristics in a robot can potentially increase performance and maneuverability, but requires finding effective solutions among an infinite set of possible morphology and controller combinations. Evolutionary computation provides a means to explore this large search space. However, developing simulation models to account for these material properties presents challenges. In this paper, we present an overview of the challenges in implementing such an evolutionary approach. We also present preliminary results demonstrating the effectiveness of our proposed methods.

Categories and Subject Descriptors

I.2.9 [**Computing Methodologies**]: Artificial Intelligence—*Robotics*

Keywords

Evolutionary Robotics, Simulation, Materials

1. INTRODUCTION

Musculoskeletal systems enable organisms to express a diverse range of movements. Individual muscles are capable of performing a wide variety of tasks, from fine motor control, to explosive movements such as jumping. Even in situations where a high level of power is required, fluid movements are achieved through complex coordination controlled by the nervous system. Additionally, secondary morphological features, such as fish fins or bird feathers, compliment the movement produced by muscles. In some cases, these secondary structures are actively controlled, but in others they are totally passive.

Observation of natural organisms leads to the question: How can similar features be realized in robots? Many robotic motors produce movement in a single axis joint, whereas natural organisms feature muscle groups that work in tandem to produce movement. Furthermore, passive material properties such as friction and flexibility, as well as passive joints, assist in locomotion and movements. Their behavior depends on complex interactions with the environment. Implementing these features in a robot requires new approaches to the hardware design process and control strategies necessary to move limbs.

In this paper, we discuss challenges associated with modeling passive and flexible materials in a digital simulation environment, as well as our approaches to address them. We demonstrate the application of evolutionary computation to harness passive properties in three different types of robots. Evolved solutions are able to exploit passive features, such as friction and flexibility, to produce effective gaits.

2. RELATED WORK

Evolutionary computation has been applied successfully in robot development since the seminal works of Sims [22] and Brooks [2]. Effective solutions have been found to address locomotion [1,5,21] and control in dynamic environments [7]. Parallels between artificially evolved robots and biological brains have been especially successful in the investigation of salamander nervous systems [10, 11], where both swimming and walking gaits were evolved, as well as mechanisms that allow smooth transitions between gaits.

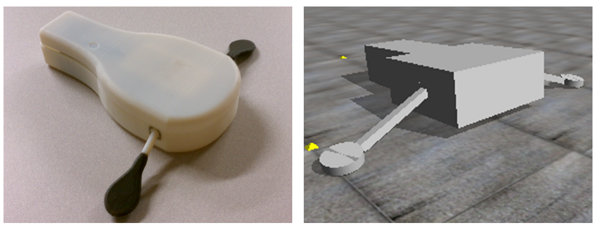
Flexible robotics, an emerging field accelerated by the advent of multi-material 3D printing technologies and advances in electroactive polymers [3], has created the need to model components beyond traditional rigid bodies. So-called soft robots are composed of flexible materials, and move by expanding and contracting their bodies [8, 9]. Results of such studies have shown that soft robots are capable of locomotion and deformation, which can be especially useful in space limited environments encountered during exploration. However, the emergence of flexible materials and passive components demands novel, efficient ways of modeling material properties in simulation environments in order to apply the evolutionary process.

3. MODELING AND CONTROL OF PASSIVE PROPERTIES

Despite the prevalence of passive properties in the natural world, modeling them in simulation is challenging. Physics simulation environments typically focus on connecting rigid bodies by joints located at the junction between two components. Moreover, the large number of candidate solutions simulated during the evolutionary process makes efficiency a critical factor. Without efficient models, simulating additional properties on top of the physics calculations can make run times for evolutionary approaches intractable. Our approach is to approximate flexible material behaviors through interconnected rigid segments and force calculations resulting in flexible, passive joints.

Modeling Flexible Materials.

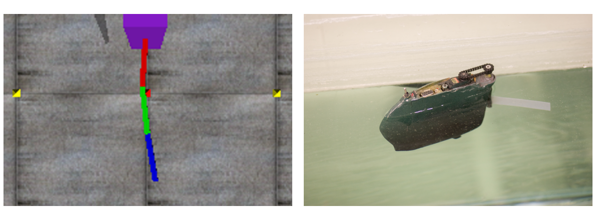
The introduction of flexible materials into a design allows solutions to harness the intrinsic properties of materials themselves. In previously published work, we focused on the development of flexible feet for a crawling robot [19]; see Figure 1. Rather than use a powered joint between arm and foot, we implemented a passively flexible joint using spring and damper constraints. The crawling robot successfully demonstrated the ability of evolution to exploit this flexibility, modeled using a spring and damper system and simulated friction. Specifically, evolved solutions favored a flexible joint between arm and foot that allowed the robot to maximize its contact area with the ground during active locomotion. Accordingly, this increased traction reduced slippage of the feet and allowed evolved solutions to travel farther per evaluation cycle than their inflexible counterparts.



(a) (b)

Figure 1: Crawling robot with flexible joint connecting arm and foot [19]. (a) 3D printed prototype. (b) Robot used in evolutionary runs.

We applied lessons learned from the above study to the development of a flexible caudal fin for a swimming robot [4]. In addition to flexibility, we employed a hydrodynamic force approximation derived in [24] to simulate an aquatic environment. Candidate solutions were simulated using the mathematical model, allowing for efficient simulations using a rigid body physics simulator. Without such a model, solutions would need to be evaluated using a more complex fluid dynamics simulator, which would make the computation time required infeasible for an evolutionary run. Evolved solutions tended towards a moderately flexible tail, as shown in Figure 2. An important aspect of this work was validating the simulation results with a physical prototype based upon the evolved solutions. Using an Objet Connex 3D printer, multiple fins were fabricated covering a range of material flexibilities. Although not a perfect transfer from simulation to reality, results exhibited a similar trend in performance, demonstrating that the method used to model flexibility in simulation was an acceptable approximation. Applying this approach in simulation allowed us to tune the parameters in an efficient manner, with an evolutionary run taking less than 24 hours with current hardware. Similar development using only physical prototypes is infeasible.



(a) (b)

Figure 2: Robotic fish with flexible caudal fin [4]. (a) Open Dynamics Engine [23] simulated model of a flexible caudal fin using three rigid segments connected by spring and dampers. (b) Physical robot used for testing 3D printed flexible caudal fins from evolved results.

Control Strategies.

Passive properties affect many facets of robotic design, accordingly, controllers must be capable of exploiting them to produce effective movements. Central pattern generators [15, 16], and more general artificial neural networks [17], are potentially well suited to incorporating these properties. Central pattern generator (CPG) networks are composed of nodes that produce a continuous oscillating signal based on internal node parameters with influence from external inputs and other connected CPG nodes. When external inputs are applied, CPGs are capable of gradually changing their output signal. Smooth transitions are especially important in robots with flexible or passive properties, since appendages are likely to deflect or bend along the limb rather than simply at a joint. For example, a flexible leg may encounter an object that causes the limb to bend, interrupting the movement unexpectedly. A controller must be able to account for this passive flexibility to successfully navigate the obstacle. Artificial neural networks (ANN) can accommodate flexible materials and passive properties in a similar manner. Specifically, ANNs generated using evolutionary methods are able to add nodes and connections that incorporate external environmental inputs to produce effective gaits. ANNs are theoretically capable of exploiting material behaviors to create effective locomotion strategies. The ability to capture material properties is essential for any control strategy in robotic systems with flexible and passive components.

4. EXPERIMENTS

In this section, we present additional data from previously published works on the crawling robot seen in Figure 1, as well as discuss the evolution of control and morphology for an amphibious robot with passive joints.

Crawling Robot with Flexible Joint.

In our first study on passive properties, we studied a crawling robot with two arms and feet that were connected by a passively flexible joint, as shown in Figure 1. Evolution was able to alter the flexibility of this joint, which in turn affected the contact area of the feet with the ground. We considered two environments, one approximating a slippery surface with low friction and a second environment with a rougher surface. Beyond the results reported in [19], here we address the effect of two environments on the evolutionary process. These first 50 generations featured a slippery environment that encouraged increased contact area with the ground to gain traction, see Figure 3. At generation 50, the second environment (higher friction), was added to the fitness calculation favoring individuals with longer arms, effectively discouraging flexibility. In this experiment, longer arms would mean a greater distance traveled per arm rotation, however, traction would be reduced. This pressure is visible in the results, as flexibility decreased after generation 50 due to the competing pressure of a higher friction environment on the joint parameters. However, the flexible joint still maintained a noticeable level of flex at the end of the evolutionary run, as the first environment encouraged feet that maximized their contact area with the ground. Results of the run provide insight into the benefits provided by passive properties. Successful individuals exhibited a preference for passive flexibility, rather than having completely stiff joints.

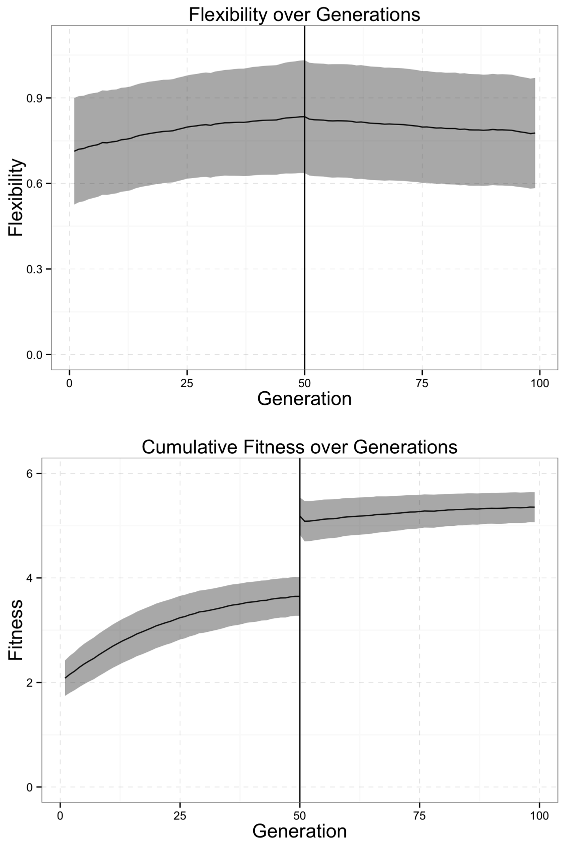
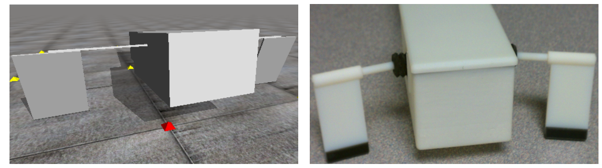


Figure 3: Evolutionary trajectory of flexibility in the crawling robot study. The top figure presents the average joint flexibility in a population over evolutionary time. As seen between the two figures, flexibility increases along with fitness up to generation 50. The addition of the second environment, denoted by the vertical line, results in a jump in fitness and a decrease in flexibility in the population. Shaded regions indicate the area between the upper and lower confidence intervals taken from 30 replicate runs.

Amphibious Robot with Passive Hinge Joint.

Our next study into passive material properties focused on evolving the morphology and control of an amphibious robot with a freely moving hinge between foot and arm; see Figure 4. An overview of this study along with additional results can be found in [20]. The passive joint on each arm allowed the fin to collapse backwards during the forward stroke, providing a means of locomotion in both terrestrial and aquatic environments. Therefore, a controller must adapt to handle the behavior of the joint indirectly. Each arm was oscillated by a servo at the base. Evolved solutions harnessed the passive joints to produce forward locomotion in both aquatic and terrestrial environments. Additionally, we found a direct relationship between control and morphology in individual solutions, indicating that evolution was able to identify the inherent characteristics of the passive joint. The controller evolved large sweeping motions of the arms, providing ample time for the fins to collapse fully backwards during the recovery stroke, and reach their fully deployed state during the power stroke; see Figure 5. Shortened strokes would potentially be harmful for this design, as fins would not reach their optimal positions, resulting in less distance traveled, the fitness metric in this experiment. A successfully evolved individual was transferred into a physical prototype, shown in Figure 4, and demonstrated effective swimming gaits. Unfortunately, the robot was unable to support itself in a terrestrial environment. However, this was due to a fabrication error in the motor interface and not a consequence of the reality gap [12, 13].



(a) (b)

Figure 4: Amphibious robot with passive joint connecting the arm and flipper [20]. (a) Simulated model used in evolutionary runs. (b) 3D printed prototype.

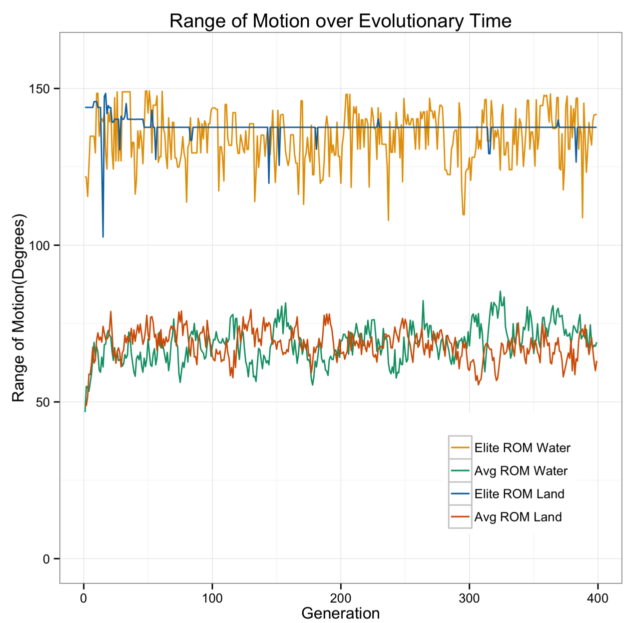


Figure 5: The range of motion that evolved over time for the passive joint robot controllers. The best performing individuals have large ranges of motion, whereas the population averages have significantly less range of motion.

5. CONCLUSIONS

Improvements in fabrication methods for flexible materials have created new areas to explore in bioinspired robotics. Novel forms of actuation and multi-material 3D printing have paved the way to create robots that harness both active and passive components to facilitate multiple behaviors. Of course, challenges have also been encountered with respect to modeling these passive properties, that must be addressed in designing simulations. In this paper, we have outlined some of the challenges faced in modeling these conditions, as well as presented some of our work investigating these properties in digital simulation. These models can help to identify and capitalize on the interactions between active and passive components in an evolutionary computation setting. Future work will further investigate modeling these properties and including them as evolutionary parameters in tasks such as station keeping, which we have previously studied with rigid component robots [18]. Additionally, incorporating passive properties into evolution, using algorithms such as Novelty Search [14] or NSGA-II [6], that allow for multiple objectives to be optimized simultaneously is planned.

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