Learning to Control Complex Tensegrity Robots

(Extended Abstract)

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ABSTRACT

Tensegrity robots are based on the idea of tensegrity structures that provides many advantages critical to robotics such as being lightweight and impact tolerant. Unfortunately tensegrity robots are hard to control due to overall complexity. We use multiagent learning to learn controls of a ball-shaped tensegrity with 6 rods and 24 cables. Our simulation results show that multiagent learning can be used to learn an efficient rolling behavior and test its robustness to actuation noise.

Categories and Subject Descriptors

I.2.6 [**Artificial Intelligence**]: Learning

General Terms

Algorithms, Design, Reliability

Keywords

Robotics, Tensegrity, Multiagent Systems

1. INTRODUCTION

Tensegrity structures are made of axially loaded compression elements encompassed within a network of tensional elements, and thus each element experiences either pure linear compression or pure tension. Individual elements can be extremely lightweight as there are no bending or shear forces that must be resisted, and they naturally distribute external forces to all of the members. Tensegrity robotics is the idea of building and controlling robots that are based on this principle. Controlling tensegrity robots faces many challenges due to complex oscillatory motions and elastic nonlinear interactions of the members.

In this paper, we present how multiagent learning can be used to control a tensegrity composed of 6 rods, 24 cables. Multiagent learning provides a smooth rolling motion and we test the best policy for different environmental conditions.

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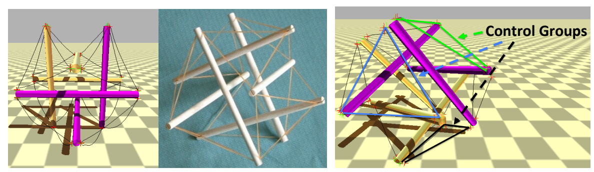

Figure 1: Structure for Tensegrity Robot

2. RELATED WORK

There are several approaches that have been taken to control tensegrity robots. Most related to the work in this paper are approaches to locomotion of tensegrity robots using evolutionary algorithms [1]. Paul et al [3] shows two different tensegrity robots that can perform a locomotion movement. These robots perform motion mostly by alternating between different configurations and doing small hops and crawling. Being able to successfully evolve these gaits is impressive given that one of the tensegrities uses only three rods, while the other uses four. However, such simple tensegrities are not able to achieve efficient rolling motion or complex dynamical movements, which is the main goal of this paper.

Recent work has been done on engineering control algorithms that leverage key features of locomotion and hand tuning of controls for rolling tensegrity robots by body deformation [2, 4]. While this work is able to produce stable smooth dynamics, they are not designed to address the oscillatory nature of tensegrities that come up at high speeds, on uneven terrain, or upon collisions with other objects that occurs in many domains.

3. LEARNING CONTROLS

In this paper we show how controls can be evolved on a ball shaped tensegrity capable of a large range of movement. To do this, we choose as our experimental platform a 6-rod, 24-cable tensegrity as shown in Figure 1. The control of the robot is done by changing the lengths of the cables. There are many possible approaches to change the length of the cables. Here, we introduce two different approaches: First, we group the cables according to their adjacency into 8 groups of 3. This approach simplifies the search space by using only 8 controllers to control the tensegrity robot. Second, we use a sinusoidal control signal to change the lengths of the cables, and the parameters of the signal are the output of the

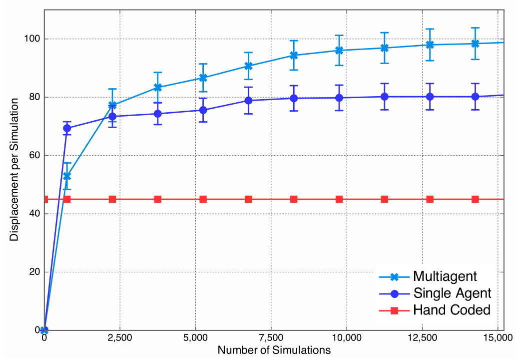

Figure 2: Results of learning to roll for the given tensegrity robot

multiagent learning algorithm. The length of each cable is calculated with the formula:

$$y(t) = C + A * sin(\omega t + \phi) \quad (1)$$

where,

- C represents the center position of the sine wave.
- A, the amplitude, is the peak deviation of the function from its center position.
- ω, the angular frequency, is how many oscillations occur in a unit time interval
- ϕ, the phase, specifies where in its cycle the oscillation begins at t = 0.

So overall control of the robot depends on 32 $(8 * 4)$ parameters that are optimized by multiagent learning. For learning we use coevolutionary algorithms.

The first experiment compares three different control policies: Hand-coded, single agent learning and multiagent learning. Figure 2 shows that both learning approaches can easily outperform the hand coded solution. The multiagent learning approach provides the best performance by moving 20% more quickly than the single agent and 100% more than our hand coded agent. Both single agent and multiagent algorithms are able to achieve smooth rolling motions

In the next experiment, we test different maximum actuation ranges for the controller. The maximum change in the rest length of a cable length is varied from 1% of the size of a tensegrity rod to 40%. Figure 3 shows that for multiagent controllers, after a 10% maximum actuation range, additional range does not gain any more advantage. On the other hand, decreasing these parameters results in robots that move less quickly. A controller that can only change its cable length 5% can only move the tensegrity at 75% of the speed compared to a controller that can change the cable length 10%.

Next, we test the multiagent tensegrity robot in an environment with different levels of actuation noise. At every time step, noise is directly added to the value of the Equation 1 that controls the length of the cables. For different noise levels, the standard deviation is set to 1%, 2%, 5%, 10%, 25%, 50%, 100% of the amplitude of the sine wave for each cable. In this experiment, we test both a policy learned

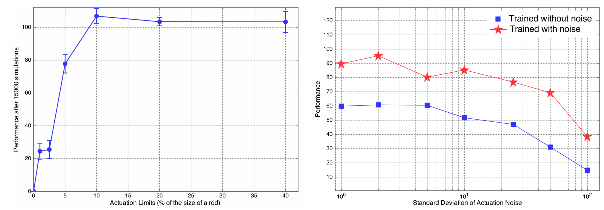

Figure 3: Robustness tests for different actuation range limitations (left) and different actuation noise levels(right)

in an environment without noise, and a policy learned in the noisy environment. Figure 3 shows that the tensegrity that is trained without noise still has tolerable performance, but its performance is significantly lower than what is is in a non-noisy environment. When we train the agents with noise, it can be seen that they can perform 50% better in low-noise environments $(1\% - 10\%)$ and 100% better in high-noise environments $(50\% - 100\%)$ than the agents that are trained without noise. This shows that the solutions generated are not highly specific to an exact model of a tensegrity and exact environmental conditions. Instead the solutions appear highly generalizable.

4. CONCLUSIONS AND FUTURE WORK

Tensegrity robotics matched with multiagent learning systems have a promising future. The structural properties of tensegrities give them many beneficial properties, while their distributed nature makes them a perfect match for multiagent systems. In this paper, we introduce a first step to this promise. We first show that in simulation a multiagent learning algorithm is able to learn an effective controller that allows a moderately complex tensegrity ball to roll. The approach proposed is able to achieve smooth rolling motion under a wide range of adverse conditions, including actuation limitations, actuation noise and cable breakage. These results show that multiagent learning systems are a strong candidate for tensegrity control. In addition, the high level of robustness may allow our multiagent framework now used in simulation to be used on our physical tensegrities now in development.

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