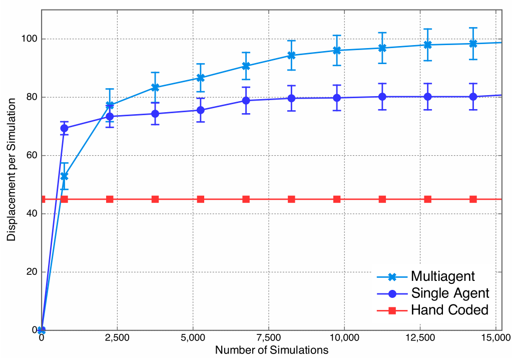


**Figure 2: Results of learning to roll for the given tensegrity robot**

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

$$y(t) = C + A * sin(\omega t + \phi) \tag{1}$$

where,

- $C$ represents the center position of the sine wave.
- $A$, the amplitude, is the peak deviation of the function from its center position.
- $\omega$, the angular frequency, is how many oscillations occur in a unit time interval
- $\phi$, 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

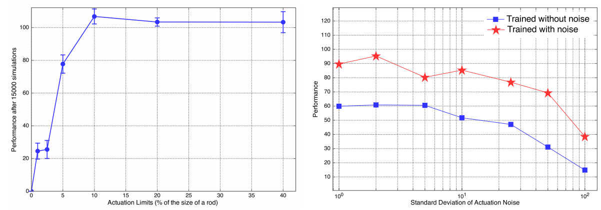


**Figure 3: Robustness tests for different actuation range limitations (left) and different actuation noise levels(right)**

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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