Paper #

Mechanical Evolution of Flexible-Legged with Reinforcement Learning

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Main Takeaway:

An actor critic RL algorithm can be used to train an agent which can define mechanical parameters of a flexible system to maximize performance given a consistent control input.

Extended Abstract:

Legged systems have many advantages when compared to their wheeled counterparts. For example, they can more easily navigate extreme, uneven terrain. However, there are disadvantages as well, including dramatically lower energy efficiency. In an effort to mitigate this disadvantage, research has been conducted that shows using flexible components in operating legged locomotive systems not only increases their efficiency but also their performance [1].

Flexible systems are highly nonlinear and are therefore difficult to develop controllers for using traditional methods. Trading flexible links for flexible joints is a mechanical solution which has been studied to solve some of these difficulties [2]. However, even though these types of systems are easier to model, they do not represent the full capability of truly flexible systems.

Because of the difficulties encountered in modeling flexible systems, control methods have been proposed that use neural networks to represent the nonlinear model of the systems and/or implement the control strategy itself. One of these methods is reinforcement learning. Beyond tasking a reinforcement learning algorithm with properly controlling the system, it can also be used to learn mechanical parameters such as the size and flexibility of links. Previous work has shown that such a method can be successful at defining both mechanical parameters and control strategies [3], [4]. In addition to methods which seek to use reinforcement learning to concurrently generate design parameters and control strategies, there are methods which use evolutionary strategies to accomplish the same goal [5].

for
In this work, rather than training both mechanical design and control strategies, a reinforcement learning algorithm is tasked with training an agent to find only mechanical parameters ~~within~~ a system that has a predetermined control input. To demonstrate the proposed method, a m~~ass-spring-damp~~er ~~environment~~
pogo stick

is used to represent a flexible single-legged system. The agent optimizes the spring constant for the given control input [6] with the objective of jumping as high as possible. ~~The reward signal used during the training of the neural networks is directly coupled to the height which the single-legged system jumps to.~~

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The initial results presented in this paper

~~Preliminary testing~~ show~~s~~ that the propos~~e~~d and results in approach produces promising results. The reinforcement learning algorithm requires little time to train ~~an agent to find better performing spring constants than a random agent finds~~. ~~A~~ ~~700%~~ jump height ~~increase~~ ~~is seen when~~ compar~~ing~~ed the ~~trained agent~~ to a random agent.

nearly an order of magnitude increase

Keywords: Reinforcement Learning, Actor-Critic, Neural Network, Flexible Systems

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