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].

However, flexible legged locomotive 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].~~ Save for full paper

In this work, rather than training for both mechanical design and control strategies, a reinforcement learning algorithm is tasked with training an agent to find only the mechanical parameters for a system that has a predetermined control input. To demonstrate the proposed method, a 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 results presented ~~in this paper~~ show that the proposed approach ~~produces~~ is a promising methods of defining mechanical parameters for flexible locomotive systems ~~given a control input~~. The reinforcement learning algorithm requires little time to train and results in nearly an order of magnitude increase in jump height compared to a random agent.

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

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