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 ~~when using legged locomotive systems~~ as well, including dramatically lower energy efficiency. A potential solution to this problem is the inclusion of non-rigid components within the locomotive system. Research has been conducted that shows using flexible components in operating legged locomotive systems not only increases their efficiency but also their performance [4]. 1 number refs in order of citation

cite series elastic actuators in full paper... maybe mention by name here

Flexible systems are highly non-linear in nature 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 the difficulties found in developing a controller for flexible systems. However, even though these types of systems are easier to model, they lack the ability to represent the full capability of truly flexible systems. a little awkward

one of these methods is reinforcement learning.

control have been proposed

that use Because of the difficulties encountered in modeling flexible systems, ~~more intelligent~~ methods are ~~studied which involve training~~ neural networks to represent the non-linear model of the systems and/or implement the control strategy itself. Beyond tasking a reinforcement learning algorithm with ~~defining an agent which will~~ properly controlling a highly non-linear system, ~~this method~~ it can be also used to ~~define an agent which can~~ learn mechanical parameters such as the size and flexibility of links. Previous work has shown that such a method used on rigid systems is successful at defining both mechanical parameters and control strategies, ~~meshing the two to allow a system to accomplish a task~~ [3], [2]. 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 [1].

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. The proposed method optimizes the design parameters so that the given control input accomplishes the task.

A mass-spring-damper environment is used to represent a flexible single-legged system, which is tasked with jumping as high as possible given a consistent input defined in [5]. An actor-critic algorithm is utilized to train an agent ~~which will~~ to modify the spring constant within the environment to ~~accomplish the task~~ maximize jump height. The reward signal used during the training of the neural networks is directly coupled to the height which the single-legged system jumps to, ~~so that the algorithm learns a spring constant which seeks to maximize the jump height. Stable Baselines defined TD3 algorithm is used to train the agent and an OpenAI type environment is used to define the environment.~~

mention in full paper, but I don't think you need to here

- preliminary results

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

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