

Mechanical Evolution of Flexible Systems 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 their ability to navigate extreme ineven terrain. However, there are disadvantages when using legged locomotive systems as well; efficient energy consumption as an example. A potential solution to this problem might be 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. Leaks

Still, the advantages are not easily gained without overcoming additional challenges. The mathematical representation of flexible systems are highly non-linear in nature and are therefore difficult to develop controllers for using traditional methods such as PID control. Using non-rigid joints in systems is a more mechanical solutions which has been studied to solve some of the difficulties found in developing a controller for flexible systems, too. However, these types of systems lack the ability to present the capability of truly flexible system.

This has brought to light the direction of using more intelligent methods involving training neural networks to represent the non-linear model of the systems and/or the control strategy itself. Using a reinforcement learning based approach to learn the weights of the networks is a popular approach and is the general approach taken in this paper. Beyond tasking a reinforcement learning algorithm with defining an agent which will properly control a highly non-linear system, it is considered that this method can be used to define an agent which can learn mechanical parameters of a system such as the size and flexibility of links.

Previous work has proven 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. In addition to

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methods which seek to utilize reinforcement learning to generate design parameters and control strategies in unison for systems, there are methods which use evolutionary strategies to accomplish the same goal However evolutionary learning is not considered further in this work.

In this work

It is proposed that rather than tasking a reinforcement learning algorithm with learning both the mechanical design and control strategy for accomplishing a task, instead task the algorithm to solely optimize the mechanical design to match a given control input. The proposed method would in theory, regardless of the given initial mechanical design, optimize that design to mesh with the given control input to accomplish 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 (paper). An actor-critic algorithm is utilized to train an agent which will modify the spring constant (k) within the environment to accomplish the task. The reward signal used during the training of the weighted neural networks is directly coupled to the height which the single-legged system jumps to, so that the algorithm learns a spring constant (k) which seeks to maximize the jump height. Stable Baselines defined TD3 algorithm is used to train our agent and an OpenAI type environment is used to define our environment.

• preliminary results

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