Paper #

Learning Optimal Control Strategies and Design Parameters for Flexible-legged Locomotive Systems

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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].

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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 tasked with learning 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 this work, reinforcement learning is used to maximize the jump height of flexible-legged locomotive systems while minimizing their power consumption. Two separate pogo-stick environments were developed ~~which were used~~ to evaluate the effectiveness of reinforcement learning for defining the control input of the system and optimizing the system's spring constant for the control input [5]. ~~Using the data collected from these experiments, the next step will be developing an environment where a reinforcement learning algorithm can be deployed to concurrently learn both mechanical parameters and the control input to maximize jump height and minimize power consumption.~~

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The results ~~presented~~ show that the proposed approach is a promising method of defining mechanical parameters and control strategies for flexible locomotive systems. A nearly order of magnitude increase in jump height is observed using a reinforcement learning agent versus a random one in the environment where the agent chooses a spring constant to match the control input. When using the environment which the agent learns a control input for the mechanical parameters of the environment, (X percentage higher jumps are seen compared to the jump heights reached using the control input described in [5])

Keywords: Reinforcement Learning, Neural Network, Control Input, Flexible Systems

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