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:

and controllers for

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 less efficient locomotion. 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, nonlinear models ~~of~~ flexible systems ~~and~~ are 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, they do not represent the full capability of truly flexible systems.

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Because of the difficulties encountered in modeling flexible systems, control methods have been developed that use neural networks to represent the nonlinear aspects of the controll~~ing~~ architecture. One of these methods is reinforcement learning (RL). Beyond tasking an RL algorithm to control the system, it can also be ~~tasked with learning~~ mechanical parameters such as the size and flexibility of links. Previous work has shown that this method can be successful at defining both mechanical parameters and control strategies for rigid systems [3], [4].

given

In this work, an RL method is used to maximize the jumping capability of flexible-legged locomotive systems while minimizing their power consumption. Two separate pogo-stick environments were developed to evaluate the effectiveness of using an RL trained agent to define the control input of the system and optimizing the system's spring constant for a control input [5]. The results show that this ~~approach~~ is a promising method of defining mechanical parameters and control strategies for flexible locomotive systems. In the environment where the RL agent finds an optimal design for a control input, a nearly order of magnitude increase in jump height is observed compared to a random agent. When observing the environment which the agent designs a control input for the mechanical parameters, higher jumping performance is also observed along with minimal control input leading to higher levels of efficiency.

Awkward
reduce energy consumption? Shorter duration control inputs?

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

References

[1] Y. Sugiyama and S. Hirai, "Crawling and jumping of deformable soft robot," *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, vol. 4, no. c, pp. 3276–3281, 2004.

[2] F. Ghorbel, J. Y. Hung, and M. W. Spong, "Adaptive Control of Flexible-Joint Manipulators," no. December, 1990.

[3] C. Schaff, D. Yunis, A. Chakrabarti, and M. R. Walter, "Jointly learning to construct and control agents using deep reinforcement learning," *Proceedings - IEEE International Conference on Robotics and Automation*, vol. 2019-May, pp. 9798–9805, 2019.

[4] D. Ha, "Reinforcement learning for improving agent design," *Artificial Life*, vol. 25, no. 4, pp. 352–365, 2019.

[5] J. Vaughan, "Jumping Commands For Flexible-Legged Robots," 2013.