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Inverse Dynamics of Cable-driven 2D Serial Linkage

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Cable-driven mechanism has been consistently attracted attention by its high payload-weight ratio, effective space utilization, and precise controllability. However, cable routing designs for precise control often sacrifice dexterity with precision, in order to fit theoretical models, which makes it difficult to take full advantage of cable driven robots. This study attempts to approach from the new perspective. This study targets serial linkages where each cable is complexly connected. A 2D hyper-redundant cable-driven linkage system was defined as an environment, and the reinforcement learning agent controlled its endpoint without having full information of the environment.

Linkage system includes 3 links (ground link, link1, link2), 2 joints (fixed joint, movable joint), 14 cables, and 8 routers. Each link is defined by length, mass, center of gravity, and thickness. Joints are modeled as damper, and have a limited range of motion. Cables are attached on links and control links by exerting force in the direction of its tension. Cables have limited range of tension, and the cable breaks when the tension exceeding the limit is exerted. Routers are intermediate points through which cables are directed. Cables can be directed through multiple links through routers, which makes a cable to affect dynamics of multiple links.

This study aims to solve the endpoint control of the extremely redundant mass spring damper system without information about the internal structure. The defined system is hyper-redundant and complexly routed to mimic human tendon system. In addition, compared to conventional mass spring damper system control, this approach is able to cope with systems with large number of inputs and stochastic outputs. This study is also expected to be applicable to optimizing number and routing of cable-driven robots.

NOMENCLATURE

θ_i= relative angle between i^{th} and $i+1^{th}$ link
R = reaction force
T = tension of the cable
h = height of the router
l = length of the link
β= angle between cable and router
a, b, c, d = router's foot position relative to parent link's origin
c = damping coefficient of joint

1. Introduction

Power transmission mechanisms such as gear, linkage, belt, ball screw, etc. are important considerations in robotics [1]. Among them, cable-driven mechanisms have the advantage of having a high payload-to-weight ratio and large workspace [2, 3, 4]. Also, they have been actively studied in various fields especially because of its high dexterity being secured from low moving mass [2].

In addition, interest in hyper-redundant manipulators has also been increasing in recent years. Hyper-redundant manipulators are systems with significantly higher degree-of-freedoms (DOFs) than DOFs that are mathematically required to move in a given environment. Since these systems are suitable for constrained environment and have high robustness, these systems are actively being studied in applications facing various environments such as industrial environments and rehabilitation robots [5-7].

However, designing the cable-driven mechanism to be a hyper-redundant is not simple. In order to control the manipulator for its intended purpose, an inverse dynamics problem should be solved. However, traditional solutions for solving the inverse dynamics, such as Lagrange-Euler equation, Newton-Euler formation, generalized d'Alembert equation, have too high computational cost to be a real-time control solution for hyper-redundant system [8]. Even though many researches are being conducted to effectively solve these equations, they have to be recalculated depending on the internal structure of the designed manipulator [9].

In this research, in order to preserve the strength of cable-driven mechanism, a reinforce learning (RL) method is introduced to solve its inverse dynamics. In the designed hyper-redundant environment simulation, even the RL model is trained without information of internal structures of the manipulator, the model successfully controls the system in real-time. With this result, we can demonstrate the suitability of RL for solving inverse dynamics of the hyper-redundant system.

2. Methods

This study constructs the hyper-redundant cable-driven linkage system, and ultimately attempts to control the system by reinforcement learning. To this end, each system components was defined, and a learning environment was constructed through system dynamics.

2.1 System Components

The cable-driven system consists of three main components: links, cables, and routers. Link is defined as a rectangular rigid object with length, mass and uniform thickness. Joint, a sub-element of the link, connects the link with the link, and is modeled with range of motion and damping coefficient.

A concept of router is introduced, which is attached vertically on a link and has the ability to route cables. Routers are attached on the front and back of the link, which allows the tension of the cable to be transmitted not only to one link, but also to be transmitted through several links.

Cable controls link through each router. The 0th router being the force source of the cable, it transmits tension as an input to routers attached on the link. Each cable has a different routing shape, and even if some cables affects the same link, their routing shape and position may be different.

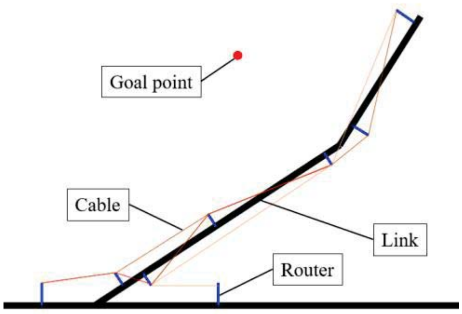

Figure 1. Cable-driven linkage system

2.2 System Dynamics

This study designs cable-driven linkage system with 3 links (including a ground link), 8 routers, and 14 cables, as shown in Figure 1. The force sources are cables, which aims to move the endpoint of the end link with mass to the desired position by controlling its tension.

Force transmission of a cable and interactions between system components can be modeled as Figure 2. The cable applies tension in its direction, and the force exerted by this tension on a link can be categorized and calculated in 2 types:

Type 1: Cable routed through 2 links

$$I\ddot{\theta} = \mathrm{T}_1 sin\beta \times h - T_1 \cos\beta \times a - F_g cos\theta - \boldsymbol{c}\dot{\theta}$$

Type 2: Cable routed through 3 links

$$I\ddot{\theta} = \mathrm{T}_1 sin\beta \times h - T_1 cos\beta \times a - F_g cos\theta_i \times \mathrm{b} + \mathrm{T}_5 \sin\alpha \times \mathrm{h}_2 + T_5 cos\alpha \times \mathrm{d} - \mathrm{R_y} \times \mathrm{l} - \boldsymbol{c}\dot{\theta}$$

The force exerted on each link by each cable is calculated every 0.001 timestep, and the behavior of the entire linkage system is simulated.

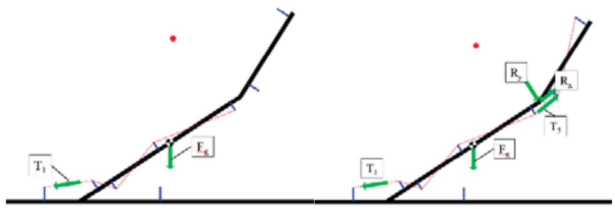

Figure 2. Type 1 (left) and type 2 (right) force exerted by different cable routing

2.3 Learning Configuration

In this study, a simulation environment is constructed to control the system and used as an environment for reinforcement learning. To simulate the behavior of real-world cable-driven linkage as similar as possible, following restrictions and input conditions were applied.

1. Range of motion is set for the joint of each link.
2. Joint of each link is modeled as a damper to reflect friction effect of real linkage.
3. Each cable's tension input is determined through random extraction with a Gaussian distribution with standard deviation of 0.005 from the actual input value to reflect error of real linkage hardware.
4. Maximum length and maximum allowable input of the cable is set, and the cable is designed to be broken when the length is longer than that or the allowable input force exceeded.
5. Similarly, maximum allowable normal force exerted in each router is set. The episode is designed to terminate with negative reward when the normal force is larger than the threshold.

This environment was implemented as a gym environment of OpenAI. The geometry of the system used in this study is shown in Table 1 and Table 2.

Table 1. Geometrical parameter of link in the system

Link 0	(ground link)	
	Sub-elements	2 routers
Link 1	Length	0.9 m

	Weight	0.8 kg
	Sub-elements	4 routers
Link 2	Length	0.5 m
	Weight	0.4 kg
	Sub-elements	2 routers

Table 2. Geometrical parameter of router in the system

Router	Parent link	Position on link	Height
Router 0	Link 0	-0.2 m	0.01 m
Router 1	Link 0	0.2 m	0.01 m
Router 2	Link 1	0.01 m	0.01 m
Router 3	Link 1	0.2 m	0.01 m
Router 4	Link 1	0.8 m	0.01 m
Router 5	Link 1	0.89 m	0.05 m
Router 6	Link 2	0.01 m	0.01 m
Router 7	Link 2	0.25 m	0.01 m

The agent does not know the full dynamics of the system, including cable routing. The agent is allowed to observe the rendered image of each timestep, θ_i, and $\dot{\theta}_i$ of each link, health of each cable (whether the cable is destructed), and error (distance between the goal point and the end point).

Action is defined as the tension applied by the first router of each of the 14 cables. Action space is composed of multi-discrete action space size of 5. That is, with the starting tension of 0, agent was to choose 5 increment or decrement of the tension. Each action is reflected by Gaussian distribution with mean of 0.1, standard deviation of 0.005.

In each episode, random goal point is defined within the possible trajectory of the end point. Each cable starts with the force of 0. At each 0.001 timestep, the force is calculated, and the chosen action is deployed to the system in every 0.005 timestep. The episode terminates after 15 seconds, or if any routers or all of the cables are broken.

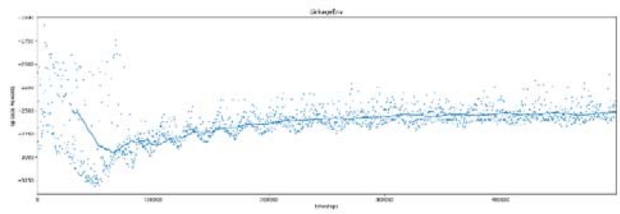

Figure 3. Learning curve of the model

3. Results

The system was implemented with OpenAI Gym and Stablebaselines3 package was used to build and train agent. PPO model was used and trained for 500,000 episodes. The learning curve of the system is shown in Figure 3.

After training, test was conducted and the model showed mean reward of -2430.75. The timestep and action was critical parameters to train the model, since the system is based on solving nonlinear differential equation, and precise control highly depends on the scale of force input.

4. Conclusions

This study solved inverse dynamics of hyper-redundant cable-driven 2D serial linkage using reinforcement learning. We present a hyper redundant linkage system that controls 3 links with 14 cable inputs, and with a concept of router, each cable is routed in various and complex ways.

In addition, the strength of the hyper-redundancy of the cable-driven system is emphasized in this study by monitoring whether each cable exceeded the limit tension, and by designing the system to destroy the cable when it does. This was also reflected in shaping reward in reinforcement learning, therefore making the agent to solve inverse dynamics considering safety.

The trained agent successfully controlled the endpoint of the link to the goal point, and its accuracy and time speed will be quantitatively measured in the future. As an object-oriented programmed backbone of this study, it is planned to be used in the future to optimize failure according to various routing of cable-driven robot.

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