CPGs for Adaptive Control of Spine-like Tensegrity Structures

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***Abstract*— An outstanding question in research of central pattern generators is whether CPGs can be used for whole body control of a robot. Given the spine's important role in walking, including a robotic spine may be a prerequisite for answering this question, but most current robots use rigid torsos. Tensegrity offers exciting possibilities for future robotic structures, as their continuous tension networks automatically distribute forces. This property creates robust structures and shows the potential to improve torsos of legged robots, and may also provide mechanisms for distributed coordination of motor patterns and entrainment with oscillatory controllers such as CPGs. Our prior work with CPGs on tensegrity structures allowed for some adaptations in rough terrain, but without feedback success was limited with larger perturbations. This work demonstrates a CPG controlled tensegrity spine with locomotor capability on additional terrains by providing feedback to the CPG.**

I. INTRODUCTION

A primary goal of bio-robotics research is to impart robots with the agile and adaptive behavior of animals. Computational models of central pattern generators (CPGs) provide a basis for some of these behaviors, including gait transitions [8], omni-directional locomotion [17], and adaptations to rough terrain [5]. An outstanding question is whether these behaviors can be extended to include whole body control of a robot. However, this is difficult to answer without including a robotic spine, since the spine contributes significantly to locomotion and whole body behavior in vertebrates [3]. Adding a spine would add several new degrees of freedom to most robots, which complicates control.

One solution is to utilize a compliant structure to simplify the control signals, a concept known as morphological computation [6]. Tensegrity structures, defined as discontinuous compression elements suspended in a continuous tension network [20], provide this compliant structure with a biological basis, and have been used to model systems ranging from the cell's cytoskeleton to the spine and shoulder girdle [9], [12], [4] (for review see [18].) Tensegrity robots have demonstrated crawling [15], [21], swimming [1], and rolling locomotion [11], and have offered many more exciting possibilities in simulation [13], [10].

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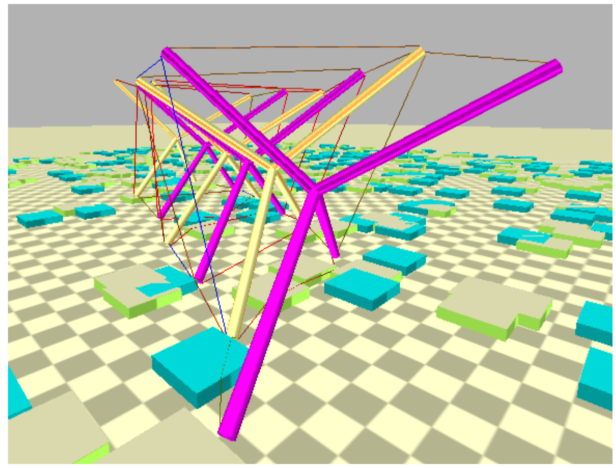

Fig. 1. One frame from the NTRT physics-based simulation showing a tetrahedral complex spine crawling over a field of randomly placed blocks.

Control of tensegrity robots inherently requires whole body coordination, since any action on the tension network influences the entire structure. Controllers for tensegrity robots tend to either be determined by evolutionary algorithms [15], [10], or use central pattern generators [1], [21]. CPGs with entrainment to sensory signals have previously been applied to a swimming tensegrity [1], and a rolling tensegrity [2]. However, as Caluwaerts et al. discuss, the sensory signals they used would be difficult to implement in hardware. Open loop CPGs are, as expected, limited in the types of terrain they can handle. This work examines a preliminary step to control of whole body motion: a crawling tensegrity spine, and uses feedback signals available to our current hardware implementations for locomotion on rough terrain in simulation.

II. CONTROL OF TENSEGRITY SPINES IN SIMULATION

A. The NASA Tensegrity Robotics Toolkit

The NASA Tensegrity Robotics Toolkit (NTRT) is an open source software package with modules for modeling, simulating, and controlling tensegrity robots[1]. NTRT uses the Bullet Physics Engine's (version 2.82) mixed linear complimentary problem solvers for rigid body dynamics, and a custom softbody spring-cable model with contact dynamics. The internal dynamics of the spring-cable are an implementation of a Hooke's law linear spring, as presented in [2]. We recently added contact dynamics to our cable model based on work by Servin et al. [19]. Collisions are detected using ghost

[1]Information, source code, and documentation for NTRT can be found at http://irg.arc.nasa.gov/tensegrity/NTRT

objects within Bullet (the cable is represented as a small cylinder), and the massless cable applies lateral forces to objects based on the sum of the internal forces along length the cable near the contact point. Motion capture tests of a single flop performed by a six strut tensegrity robot validated the rigid body and internal cable dynamics within 1.3% error on position [2], hardware validation of the contact dynamics is future work.

In addition to physics simulation, NTRT contains libraries for controllers, including CPGs, machine learning, and low level actuator dynamics.

B. Tensegrity Spine Model

The tensegrity spine used in this work is based on the 'tetrahedral complex' for vertebrae, which was originally developed as a static model by Tom Flemons [4], and is shown in Figure 1. The vertebrae consist of four rods that meet at a central point, as if they were drawn from the center of a tetrahedron to its verticies. When stacked in a tension network, they make a stable yet flexibile column through tetrahedral 'saddle joints.' To create a tensegrity robot, we assume all of the cables are individually actuated. In hardware, actuation typically takes the form of a cable wrapped around a spool on a rotary DC motor, as in [21], [13]. We chose the tetrahedral complex because in prior work it displayed the most efficient locomotion [13], and upon additional tuning, displayed the fastest locomotion of the morphologies we have examined so far. For this work we used a six segment spine, to reduce the computational time for contact dynamics and make the terrain features more difficult compared to a longer spine. Each rod was assumed to be 10 cm long, resulting in a 57.5 cm long robot.

C. Control Methods

To control the cables of the tensegrity spine, we use a distributed formulation of impedance control. The first formulation of impedance control was originally developed for serial chain manipulators [7]. In its distributed form, the equation becomes scalar, but provides control on both length and tension [14], and tunable stiffness. The equation is as follows:

$$T = T_0 + K(L - L_0) + B(V - V_0) \tag{1}$$

Where T is the tension setpoint sent to the motor's PID controller, T_0 is a tension offset, K is a position gain on the difference between the cable's current actual length L and desired length L_0. B serves a similar function for V and V_0, where V_0 is a control input from the CPGs or sine waves (in Orki et al.'s implementation V_0 is always zero [14], [21]).

Each node of the CPG corresponds to one cable of the tensegrity spine, for this case the CPG has 40 nodes. The specific CPG equations we use are a combination of the adaptive phase-coupled oscillator equations of Righetti et al. [16] (feedback on the frequency) and Gay et al. [5] (feedback on the amplitude and phase):

$$\dot{r_i} = \gamma(R_i + k_r F_r - r_i^2) r_i \tag{2}$$

$$\dot{\theta}_i = \omega_i + k_\theta F_\theta + \sum_j r_j w_{ij} sin(\theta_j - \theta_i - \phi_{ij}) \tag{3}$$

$$\dot{\omega_i} = k_\omega F_\omega sin(\theta_i) \tag{4}$$

$$V_i = r_i(cos(\theta_i)) \tag{5}$$

where r_i is the amplitude of the wave, ω_i is the frequency, θ_i is the phase, and V_i is the input to the impedance controller. The amplitude is set by convergence parameter γ, and setpoint R_i, the phase relates to connected nodes through weight w_{ij} and phase offset ϕ_{ij}. The terms k_r, k_θ, k_ω are scalar gains on feedback functions F_r, F_θ, and F_ω, which, similar to [5], are the output of an artificial neural network. In this case, the network's inputs are the length and tension of the cable for each respective CPG node. The network has two nodes in the input layer, four in the hidden layer, and three in the output layer. The same network is reused for each cable and CPG node, providing sensory feedback.

To determine the connectivity of the CPG, we used the same methods as our prior work, where each node is connected to nodes that share a rigid body, based on their respective cables [13]. In this case, with eight strings between segments, nodes in 'middle' cable groups would connect to 23 other nodes, and those on the 'ends' would connect to 15. Symmetry rules discussed in [13] are used to limit the total number of parameters, in this case 205 are required to specify the amplitude, frequency, weights, phase offsets, and feedback parameters of the CPG.

D. Machine Learning

In order to determine a controller for rough terrain, we tuned and tested the tensegrity spine on three types of terrain: flat ground, sinusoidal hills with an amplitude of 2 cm, and a field of 500 randomly placed blocks. The blocks were 5 cm wide, 0.5 cm tall and were fixed to the ground within a 200 cm by 200 cm area around the origin. Trials were evaluated according to distance traveled in 60 simulation seconds. If multiple terrains were used, scores were averaged.

Given the large number of parameters, we started tuning our system by selecting the best gaits for an open loop CPG on flat ground from 24,000 Monte Carlo trials. The eight best were selected for a Gaussian sampling hill climbing optimization on all three terrains, where random samples are taken from a narrow distribution around the best results. The hill climbing step improved the results between 100% and 200% over Monte Carlo, but most of the improvement was on flat ground, indicating the need for feedback to the CPG (the feedback functions were zero during the preceding steps).

In order to adapt the CPG to varying terrains, we provided feedback using an artificial neural network as described in section II-C. To parameterize the network, we used a genetic algorithm with crossover, mutation, and elitism. The population consisted of 60 members, the best 15 of which survived to the next generation. Fitness was again determined by average score between the three terrain types (hills, blocks, flat ground). Evolution for the feedback parameters ran for 14 generations (1,935 trials), the CPG parameters were held constant during these trials.

III. RESULTS

Once the feedback functions were tuned, we compared the performance of the closed loop CPG controller to our previous open loop configuration, impedance control was used in both cases. Flat ground and hilly terrain results were both deterministic, and are summarized in Table I, block field results are summarized in Figure 2. While for this gait, feedback slows locomotion on flat ground by about 1%, the robot's ability to handle rough terrain improves significantly.

TABLE I
RESULTS FROM DETERMINISTIC TERRAIN TYPES

Terrain	Without Feedback	With Feedback
Flat Ground	492.8 [cm]	487.1 [cm]
2 cm Hills	30.4 [cm]	105.3 [cm]

To determine the robustness of these results, we set up twenty different block fields using the same random seed and tested the robot's performance with and without feedback[2]. Since the robot starts at the center of the square block field, if it traveled at least 150 cm, it is guaranteed to have 'escaped' the block field. The controller with feedback moved further than the open loop controller in all cases, and 'escaped' in 17 out of 20 trials.

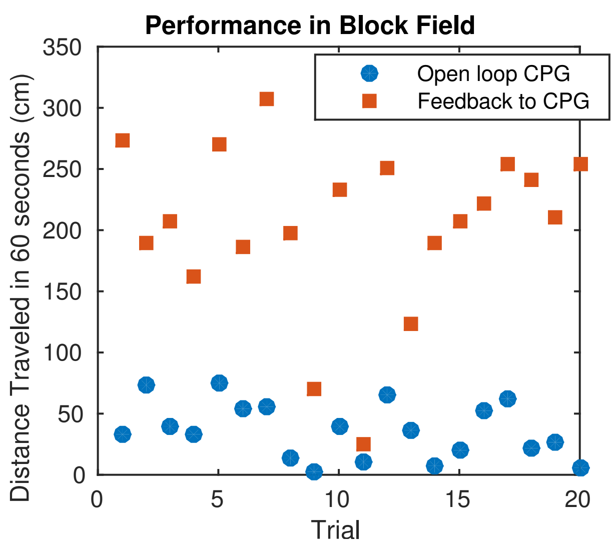

Fig. 2. Tests of locomotion on a random block field with and without feedback at the CPG level, using the same random seed.

IV. CONCLUSIONS AND FUTURE WORK

These results indicate that (1) distributed, proprioceptive feedback is sufficient to improve the performance of a CPG controller on rough terrain, and (2) CPGs are a strong candidate for control of spine like tensegrity structures, and may have potential for controlling whole body motions. Future work will include feedback from contact sensors, heading information for goal directed locomotion, explore schemes for reduced actuators, and explore the role of tensegrity spines in quadruped locomotion.

[2]Video: `https://www.youtube.com/watch?v=94yqYPUYjH0`

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