



Title	Using bio-inspired physical interaction to plan and control robots to traverse cluttered large obstacles
Author(s)	Xuan, Qihan; Li, Chen
Citation	The 9.5th International Symposium on Adaptive Motion of Animals and Machines (AMAM2021). 2021, p. 49
Version Type	VoR
URL	https://doi.org/10.18910/84889
rights	
Note	

The University of Osaka Institutional Knowledge Archive : OUKA

<https://ir.library.osaka-u.ac.jp/>

The University of Osaka

Using bio-inspired physical interaction to plan and control robots to traverse cluttered large obstacles

Qihan Xuan, Chen Li

Johns Hopkins University, Maryland, United States

qxuan1@jhu.edu, <https://li.me.jhu.edu/>

1 Introduction

When current vehicles and robots encounter obstacles, their primary way of “traversal” is to plan and follow a trajectory that safely avoids all obstacles using a geometric map of the environment. For this to work, physical interaction with the environment is usually well understood (e.g., wheeled-ground interaction [1]) and the robot’s motion can be well controlled (e.g., legged locomotion on near flat surfaces [2]).

However, when the obstacles are too dense to avoid (forest floor [3], building rubble, etc.), or normal locomotor mode does not work on some grounds (the slippery ground [4], the granular terrain [5], etc.), current robots cannot traverse complex terrain successfully without having effective interaction with obstacles/ground.

On the other hand, animals can move through such complex terrain using physical interaction with obstacles. Physical interaction depends on environmental physical properties like material properties, internal structure, mass distribution etc. of the obstacles. Thus, to traverse complex terrain like animals, environmental physical properties are useful for robots. Here, we built a bio-inspired, beam traversal model to demonstrate how we obtained stiffness and bending positions of beams using force sensing during physical interaction and used this information to plan and control the system to traverse beams.

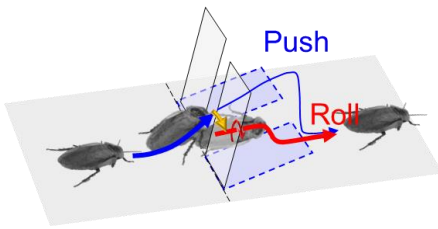


Figure 1: Cockroach beam traversal experiments show that the cockroach has two main strategies to traverse the beams: 1. Pushing down beams (blue curve). 2. Rolling its body (red curve).

2 Previous work

In a previous study, we studied the behavior of a cockroach encountering flimsy beams and stiff beams [6]. The experimental results showed that the more desirable traversal strategy depended on the stiffness of beams. When the beams were flimsy, the cockroach simply pushed down the beams to traverse (Fig. 1, blue curve). When the beams were stiff, this

became much more costly due to a high potential energy barrier. Instead, the cockroach collided with the beams and stopped, and then rolled its body to traverse the gap (Fig. 1, red curve), which substantially reduces the cost as the potential energy barrier is much lower. However, from geometric information of the obstacles alone, the cockroach would not be able to differentiate stiff and flimsy beams. Thus, it is likely that they use physical interaction to sense how stiff the obstacles are and use this information to inform their strategy in traversing. Similarly, doing this would help robots traverse more effectively and efficiently.

3 Model Design

For simplicity, we modelled the cockroach, the beam, and their contact using the approximations below.

The cockroach was approximated as an ellipsoidal rigid body driven by a propulsive force F , which was constant before control (Fig. 2A, the thick, black arrow). We used Euler angles (yaw γ , pitch β , roll α , $Z-Y-X$ Tait-Bryan convention) to define 3-D rotation. We restricted the body to only translate in the forward x direction and rotate in roll and pitch directions to reduce the degrees of freedom to simplify model analysis.

The beams were approximated as massless plate segments with no thickness. Each beam consists of two rigid segments with a torsion spring at the middle joint, which approximate cantilever bending of a grass-like beam (Fig. 2B). The bottom segment is upright, and the distance of joint from ground is Δh . Thus, each beam has two unknown parameters: the stiffness k of the spring and the bending location Δh , which need to be solved from contact forces.

We approximated all body-beam contacts to be quasistatic and neglected the friction between the beams and the body. Contact forces were normal to the tangent planes of the contact points on the ellipsoidal body (Fig. 2A).

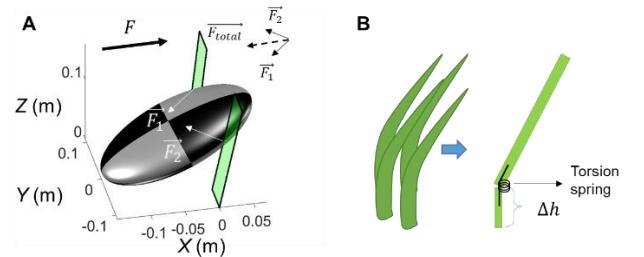


Figure 2: Cockroach beam traversal model design. (A) Cockroach is assumed as an ellipsoidal rigid body. F is the propulsive force. $\vec{F}_1$

and $\vec{F}_2$ are contact forces from each beam. $\vec{F}_{total}$ is the sum of the contact forces. Position x of beams is $x = 0$ m. (B) Beam model. A torsion spring is used as connection. The bottom segment is upright, and its length Δh is constant.

4 Solving for physical interaction

The stiffness k and Δh of the beam were set, but the ellipsoidal body did not know them until they were solved from data of force sensing. When the body contacted the beams, we calculated the total forces $\vec{F}_{total}$ that the beams exerted on the body based on the model (Fig. 2A). Gaussian noise was added to $\vec{F}_{total}$ to simulate the sensing forces $\vec{F}_{sensing}$ measured from sensor that are noisy. The body sensed and sampled $\vec{F}_{sensing}$ after contact.

The sampled data of $\vec{F}_{sensing}$ were used to solve the unknown variables. An error function was defined as the sum of the mismatch between the total forces $\vec{F}_{total}(k, \Delta h)$ with unknown variables and the sensed forces $\vec{F}_{sensing}$. By minimizing the error function, the values of unknown variables were solved.

5 Motion planning and control

Knowing the stiffness and bending position of beams helps in motion planning and control through potential energy landscape. Potential energy landscape of a similar beam traversal model was introduced in a previous work [6], which combined the geometric map and the stiffness of beams. Given the solved values from Section 4, we calculated the 3D potential energy landscape of our model system. We created a dual-direction network based on the potential energy landscape (Fig. 3A). We defined the states in the potential energy landscape as vertices. Edges connected vertexes. We defined energy cost of the edge as the potential energy difference if the body moved to the higher potential energy state; in the counter direction, the energy cost was 0 J (Fig. 3A). The defined energy cost quantified the difficulty of traversal. The desired trajectory for motion planning was the one with minimum cost [7] (Fig. 2B).

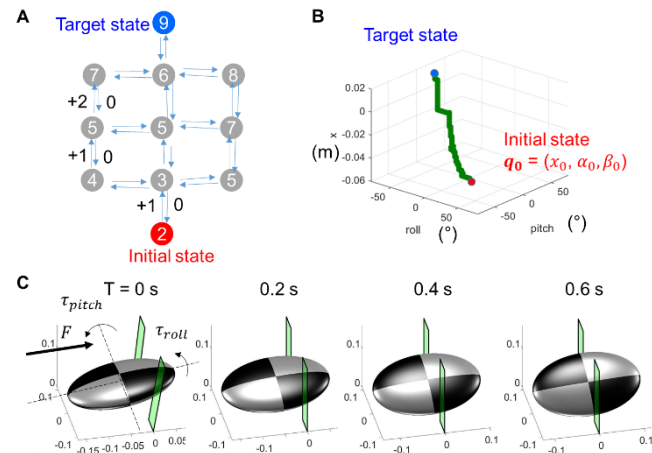


Figure 3: Motion planning and body control. (A) Schematic of the dual-direction network based on the potential energy landscape. Number in circles means potential energy. Blue arrows represent

edges and the number next to the edge is cost. (B) The minimum cost trajectory of an example trial. (C) Snapshots of the body traversal under control. Control signals consist of the propulsive force F , pitching torque τ_{pitch} , and rolling torque τ_{roll} .

Based on motion planning, we used the feedback linearization control [8] to track the planned trajectory (Fig. 3C). It shows that the motion planning gives the same rolling strategy as cockroaches traversing when encountering the stiff beams. Without active control, the body pitches up and can become stuck in front of stiff beams. This is because the forward, propulsive force can be insufficient to push down stiff beams and the kinetic energy fluctuation is insufficient to overcome the potential energy barrier that must be overcome to for the body to roll [6]. Our work showed that motion planning and active control using sensing of interaction physics can help the body more easily traverse the beams.

6 Summary and future work

We developed a beam traversal model to demonstrate that locomotor-terrain physical interaction parameters can be recovered from the force sensing and can be used to do motion planning and control to better traverse the beams. In the motion planning above, we only considered the change of potential energy. Our next step is to consider the effect of inertia in motion planning and further improve the traversal performance.

7 Acknowledgement

This work was supported by an Army Research Office Young Investigator award, a Burroughs Wellcome Career Award at the Scientific Interface, and The Johns Hopkins University Whiting School of Engineering start-up funds to C.L.

References

- [1] H. Pacejka, *Tire and vehicle dynamics*. Elsevier, 2005.
- [2] R. Altendorfer *et al.*, “RHex: A biologically inspired hexapod runner,” *Auton. Robots*, vol. 11, no. 3, pp. 207–213, 2001.
- [3] C. Li, A. O. Pullin, D. W. Haldane, H. K. Lam, R. S. Fearing, and R. J. Full, “Terradynamically streamlined shapes in animals and robots enhance traversability through densely cluttered terrain,” *Bioinspiration and Biomimetics*, vol. 10, no. 4, 2015.
- [4] F. Jenelten, J. Hwangbo, F. Tresoldi, C. D. Bellicoso, and M. Hutter, “Dynamic Locomotion on Slippery Ground,” *IEEE Robot. Autom. Lett.*, vol. 4, no. 4, pp. 4170–4176, 2019.
- [5] C. Li, P. B. Umbanhowar, H. Komsuoglu, D. E. Koditschek, and D. I. Goldman, “Sensitive dependence of the motion of a legged robot on granular media,” *Proc. Natl. Acad. Sci. U. S. A.*, vol. 106, no. 24, p. 9932, 2009.
- [6] R. Othayoth, G. Thoms, and C. Li, “An energy landscape approach to locomotor transitions in complex 3D terrain,” *Proc. Natl. Acad. Sci. U. S. A.*, vol. 117, no. 26, pp. 14987–14995, 2020.
- [7] D. B. Johnson, “A Note on Dijkstra’s Shortest Path Algorithm,” *J. ACM*, vol. 20, no. 3, pp. 385–388, 1973.
- [8] J. Chiasson, “Dynamic Feedback Linearization of the Induction Motor,” *IEEE Trans. Automat. Contr.*, vol. 38, no. 10, pp. 1588–1594, 1993.