

Dexterous Legged Locomotion in Confined 3D Spaces with Reinforcement Learning

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Background

Prior deep RL-based locomotion controllers primarily focus on

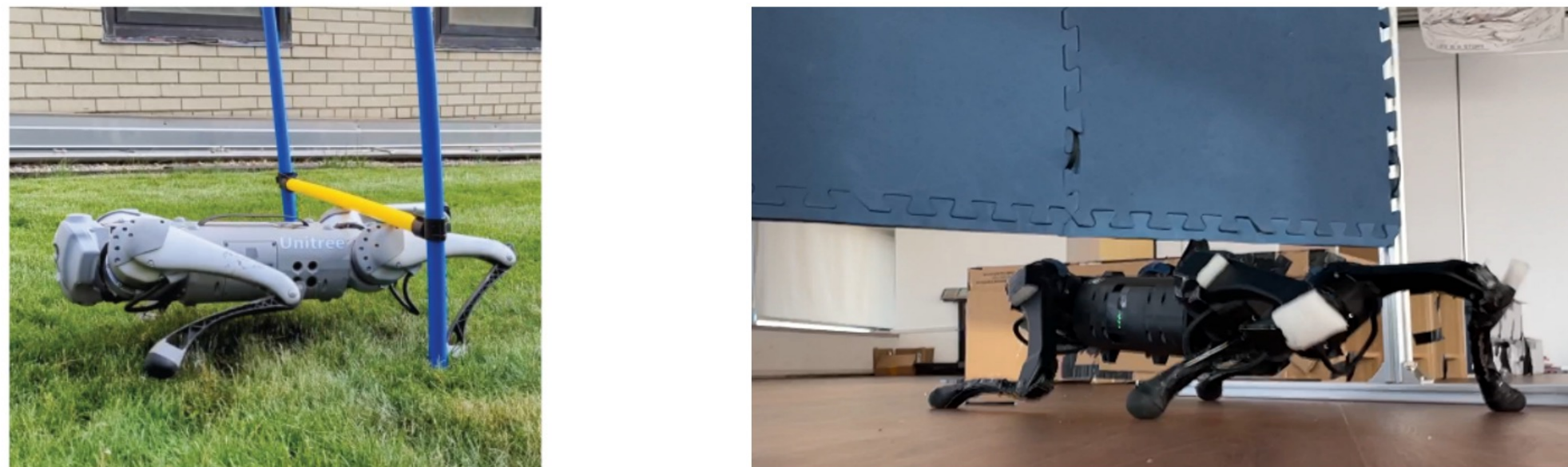
- constraints underneath the robots:



Rudin, Nikita, et al. 2022

Agarwal, Ananye, et al. 2023

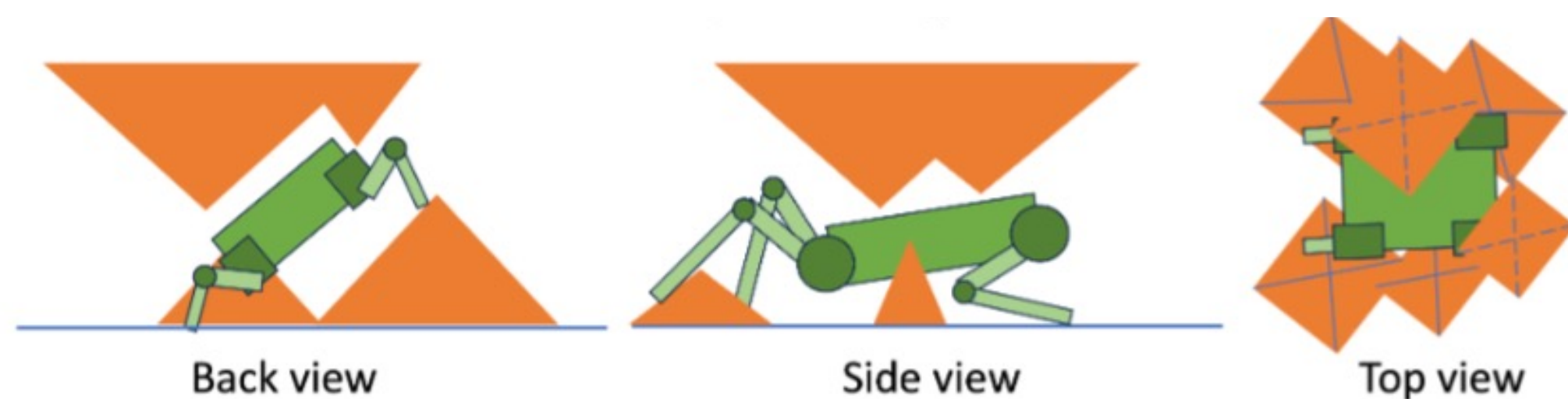
- or simple handcrafted top constraints:



Margolis, Gabriel B., et al. 2023

Zhuang, Ziwen, et al. 2023

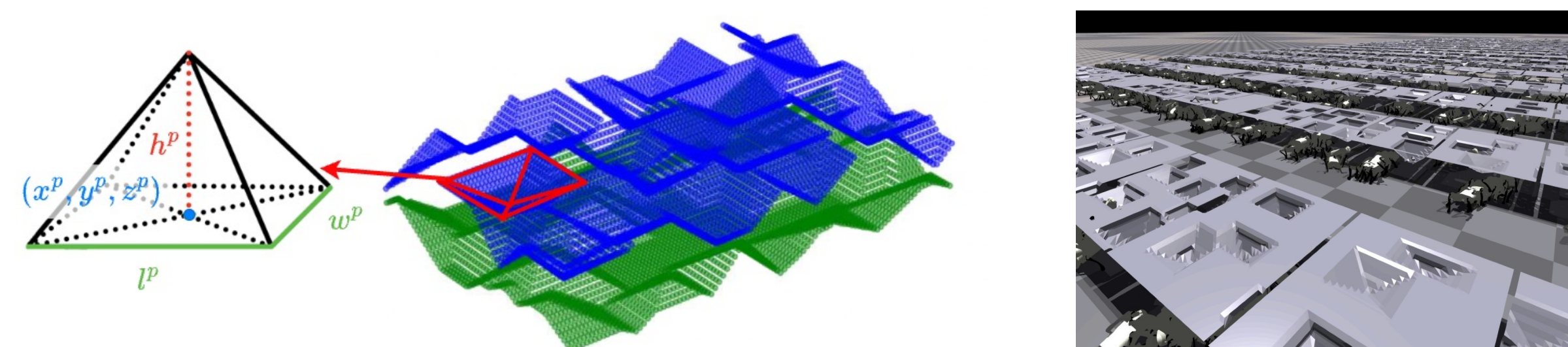
3D constraints need **acyclic** and **asymmetric** limb movements.



Goal: an RL-based locomotion controller that can perform agile and robust locomotion in diverse and confined 3D spaces

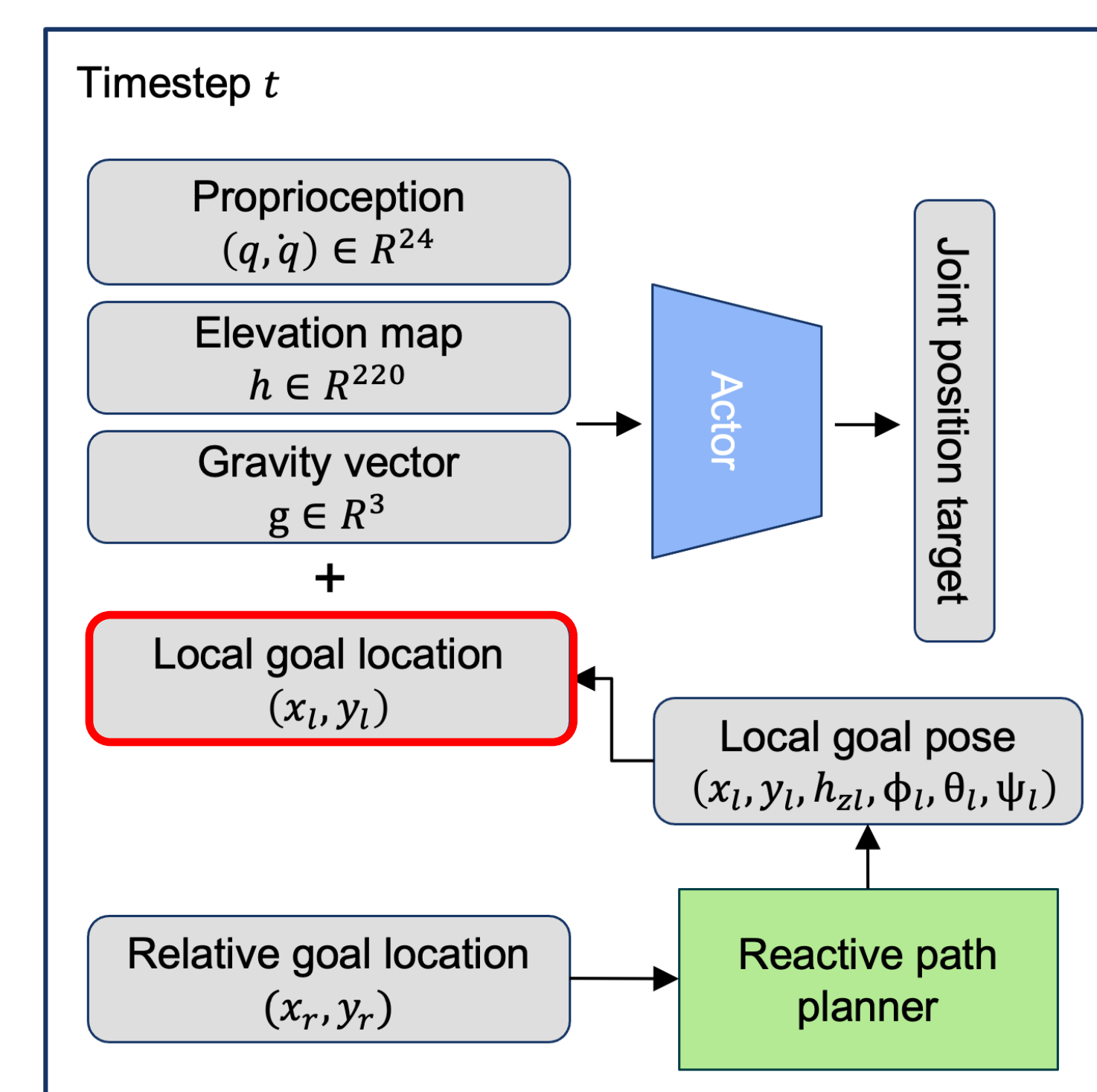
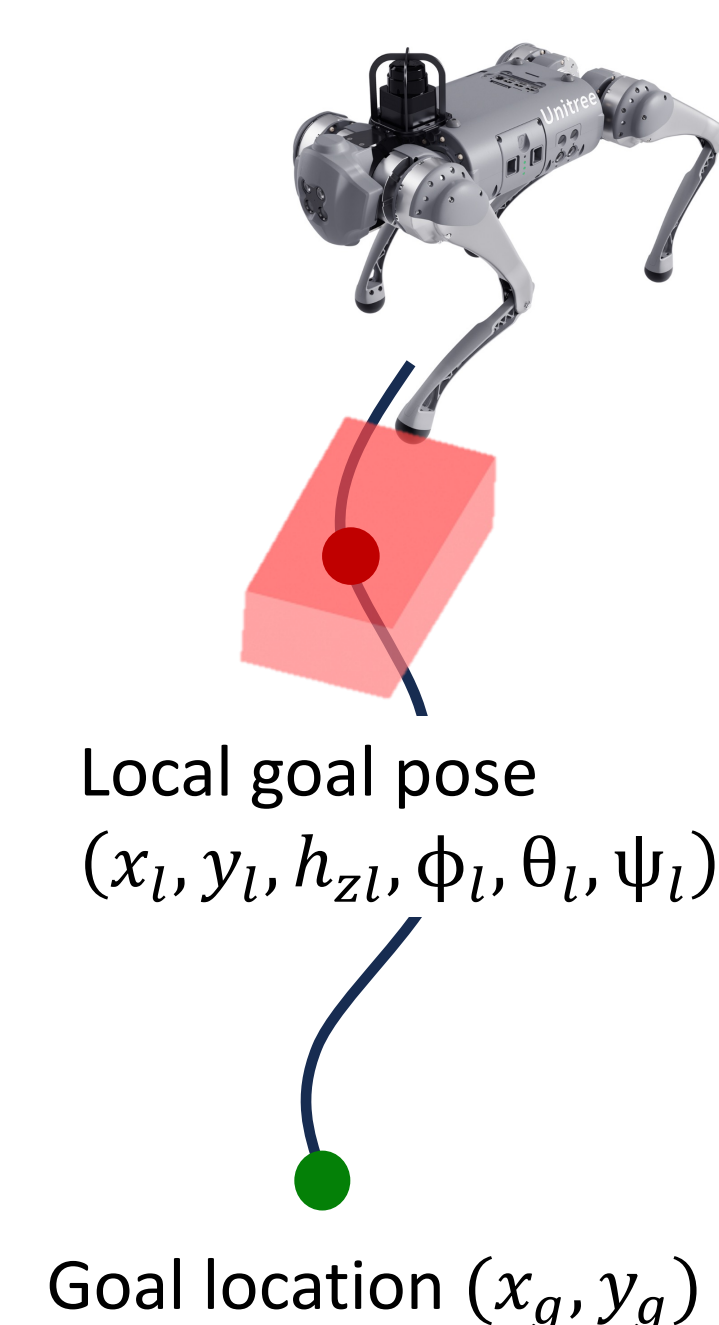
Tunnel Environments

- A tunnel environment is represented by both the ceiling (blue) and the floor (green) as a $n_r \times n_c$ pyramid matrix.
- Each pyramid has random height, width, length, and position.
- Enable parallel simulation by IsaacGym.



We develop an RL-based **hierarchical system** that enables legged locomotion to handle environments with not only underneath constraints, but also **all-around constraints**.

Hierarchical Dexterity



Results

1. Success Rate:

Approach	Easy	Medium	Hard
End-to-end dexterity	29.4%	7.0%	5.1%
Hierarchical dexterity (ours)	96.8%	51.5%	39.4%
Parameterized motor skills	65.7%	4.0%	2.4%

2. Sample Efficiency:

Approach	#timesteps to convergence
End-to-end dexterity	600 million
Hierarchical dexterity (ours)	40 million
Parameterized motor skills	80 million

3. Collision Count:

Approach	Easy	Medium	Hard
End-to-end dexterity	7.9	16.2	29.8
Hierarchical dexterity	3.8	32.3	43.6

As indicated by the contact counts, the robot has to make more contacts in harder environments, for example, lean against some obstacles to assure torso stability and forward progress.

Takeaways

- Robust locomotion in confined 3D spaces only emerges in hierarchical dexterity by training to reach local goal locations computed by a classical path planner.
- Parameterized motor skills are not sufficient to navigation in confined 3D spaces. The agent has to develop its own motions to reach the local goals.
- Generalizing to diverse and confined 3D spaces is still challenging.

Acknowledgments

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