

Learning robust autonomous navigation and locomotion for wheeled-legged robots



Group 08

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Overview

Motivation and Challenges

■ Motivation

- Efficient last-mile delivery in urban areas
- Fast and efficient on flat ground and able to overcome obstacles like stairs

■ Challenges

- Static and dynamic obstacles avoidance
- Fully integrated navigation and locomotion
- Adaptive gait selection and locomotion control over various terrains (stairs, grass, slopes)
- Cannot be inspired by nature

i. Pedestrians



ii. Obstacles and Terrains



Technical details

The robot

- **Wheeled-Legged Quadruped Robot (ANYmal)**
- **Sensors**
 - 3 LIDARs: Terrain mapping and Localization
 - Stereo Camera: Dynamic obstacles detection
 - GPS: Unused
 - IMU and Joint encoders
- **Control**
 - Joint position control: PD
 - Wheels velocity control: PD



<https://newatlas.com/robotics/swiss-mile-transformer-robot/>

Technical details

Localization and path planning

- **Environment previously scanned with laser scanner**
 - Create mesh of the city from point cloud
 - Create navigation graph
- **Dijkstra algorithm on navigation map to choose path**
- **LIDAR sensors to localize inside mesh**
 - More robust than GPS
 - Still problems with long corridors as stereo camera cannot see far away

A Workflow

i. Scan the environment



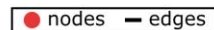
Laser scanner

ii. Process point cloud

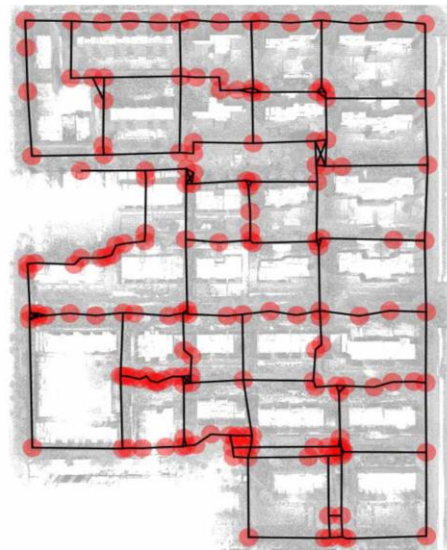


Collection time: ~90 min.

ii. Navigation graph

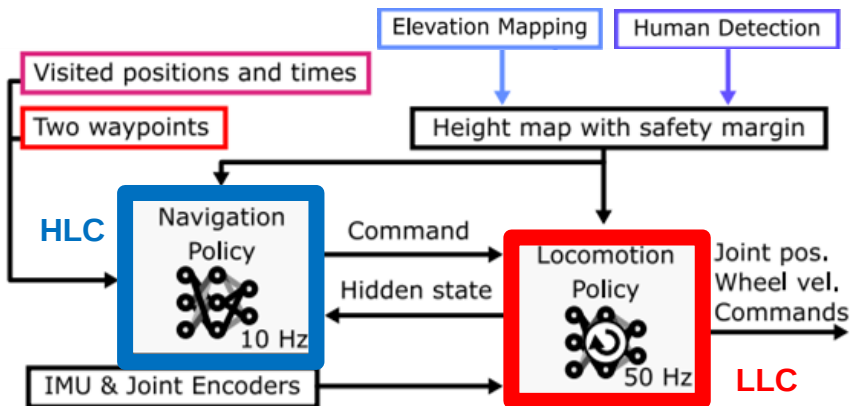


Path planning
(Dijkstra search)



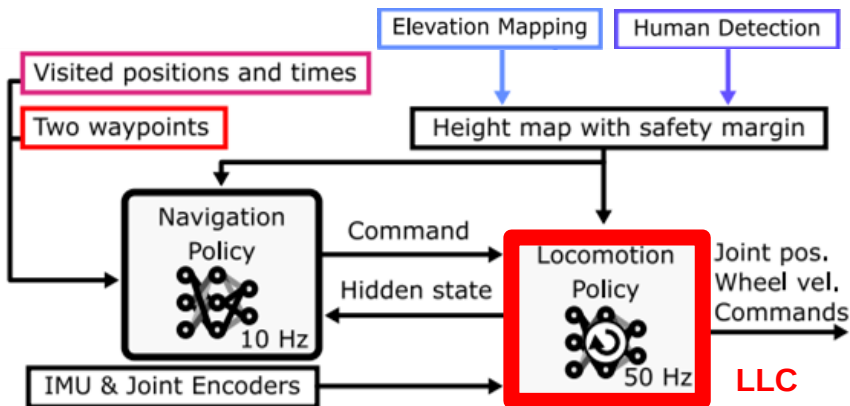
Two controllers

- High-Level Controller (HLC)
- Low-Level Controller (LLC)
- Both neural networks trained with model-free reinforcement learning
- Trained sequentially, starting from the LLC



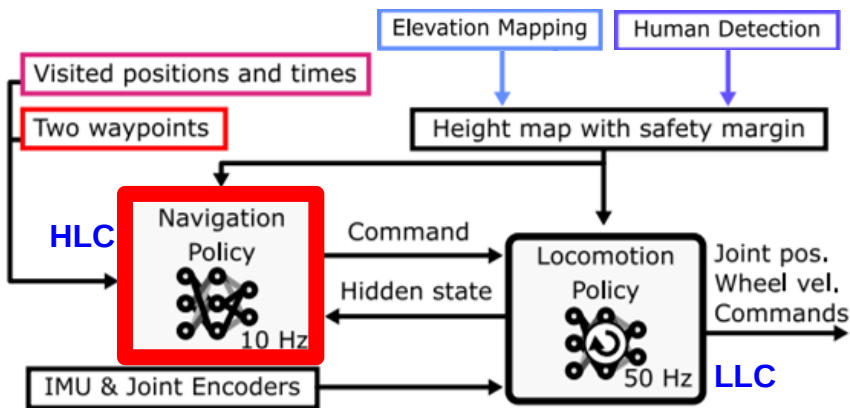
Low-Level Controller (LLC)

- **Output**
 - Velocity tracking
 - Gait choice
 - Mode transition(walking/driving)
- **Neural network trained in two steps**
 - **Teacher policy**
 - Follows random velocities on rough terrains
 - Privileged information (Robot's motion, terrain properties, noiseless exteroceptive measurements)
 - **Student policy**
 - Noisy measurements (IMU, joint states, height, ...)
 - Learning from the teacher
 - Reward: velocity tracking

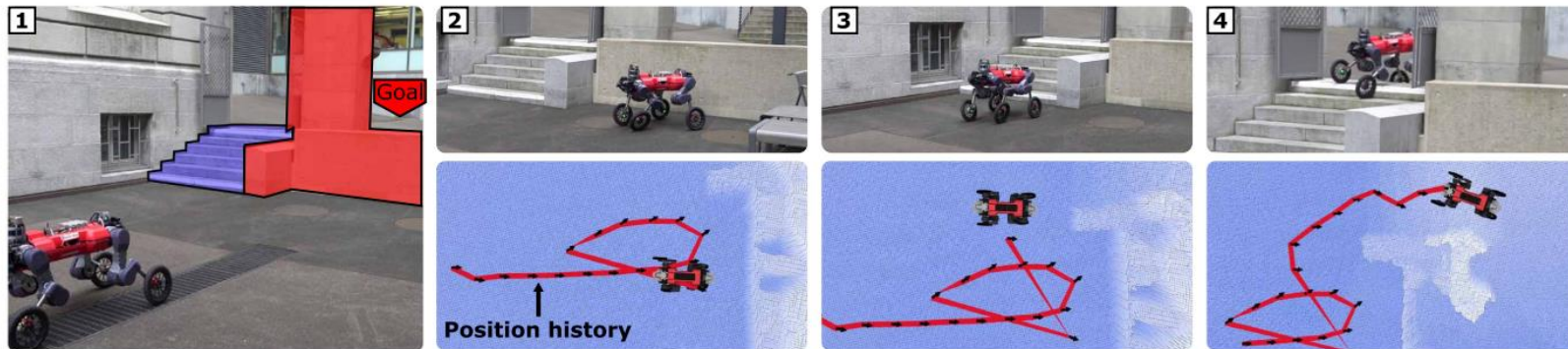


Mobility-aware navigation controller (HLC)

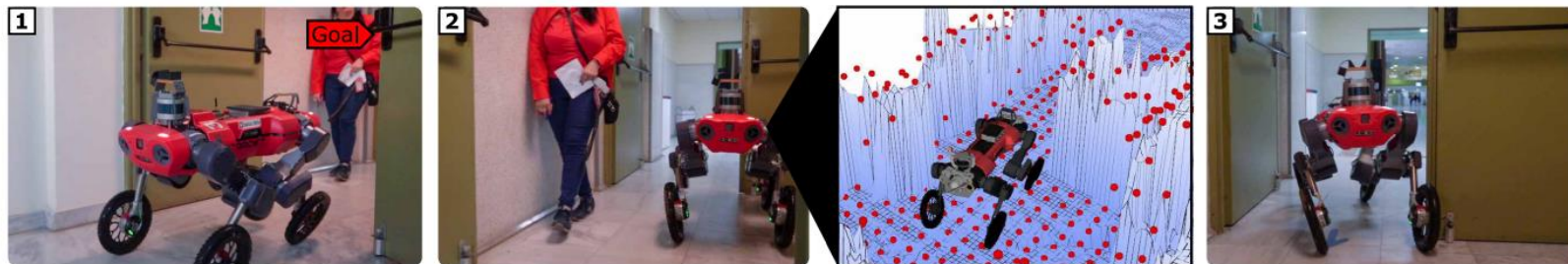
- Computes velocity targets at high frequency
- Bounded action space (hard constraints on output)
- Rewards:
 - Smallest distance to waypoint
 - Bonus on exploration



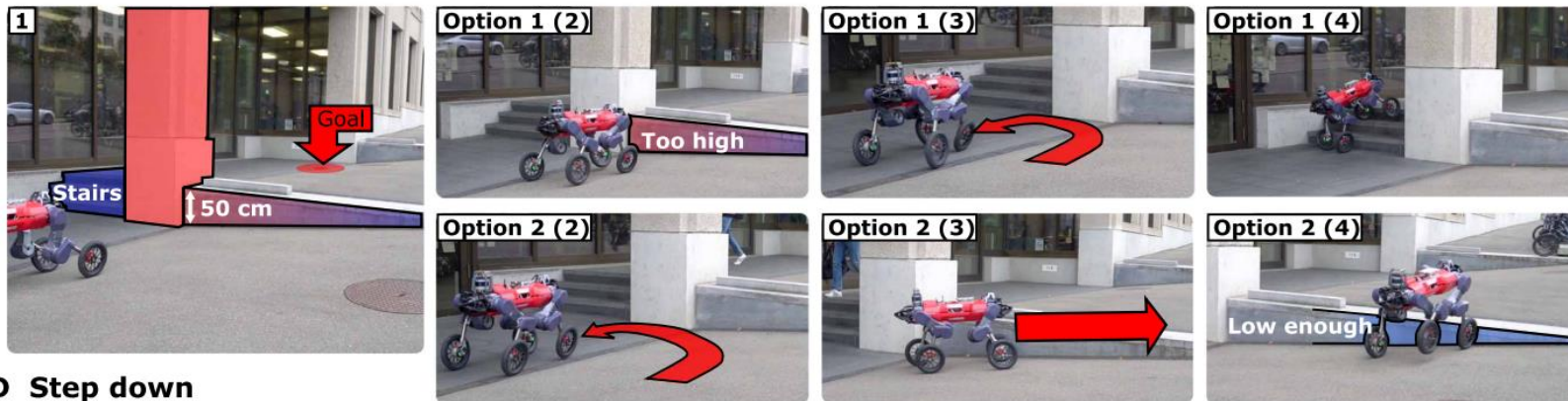
A Detour



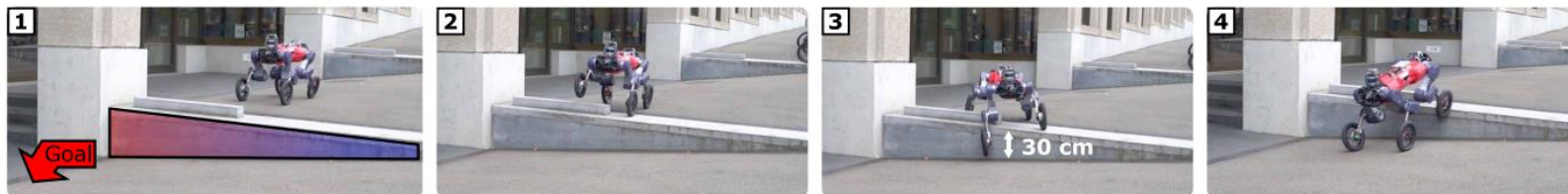
B Narrow space



C Complex obstacle



D Step down



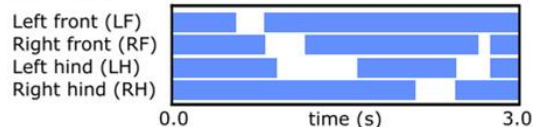
E Human safety



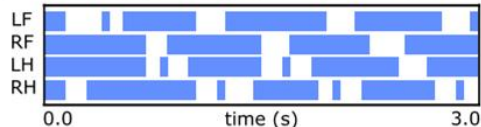
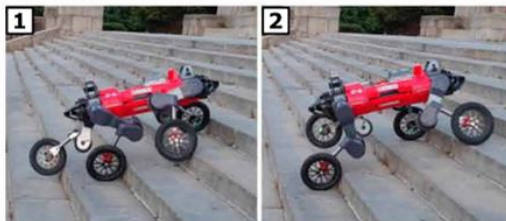
Results

Gaits on different terrains

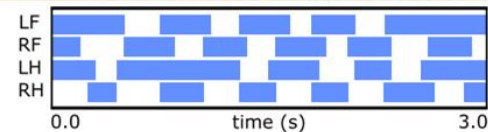
i. High step



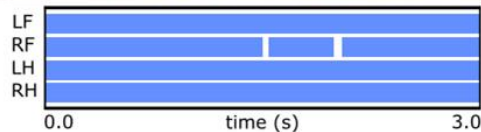
ii. Stairs



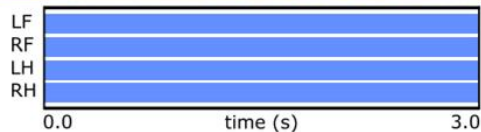
iii. Uphill



iv. Uneven ground



v. Downhill

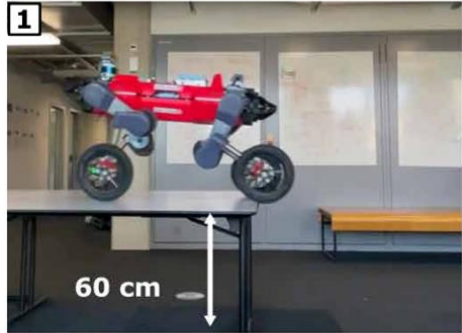


■ Wheel in contact with the ground
□ Wheel in the air

Results

Extreme obstacles

i. Large step down



ii. A block



Results

Comparison with Legged robot

	Wheeled-legged	Legged
Average speed	1.68 m/s	0.55 m/s
COT Cost of transport	0.17	0.34

$$COT_{\text{mech}} = \sum_{\text{all joints}} [\tau \dot{\theta}]^+ / (mg |v_{xy}^b|)$$

Joint torque $\nearrow$ τ
 Joint speed $\nearrow$ $\dot{\theta}$
 total weight $\nearrow$ mg
 robots horizontal speed $\nearrow$ $|v_{xy}^b|$

Results

Comparison with baselines

- Controllers:
 - Controller
 - Controller without memory
 - Baseline (legged)
- 10 experiments / controller

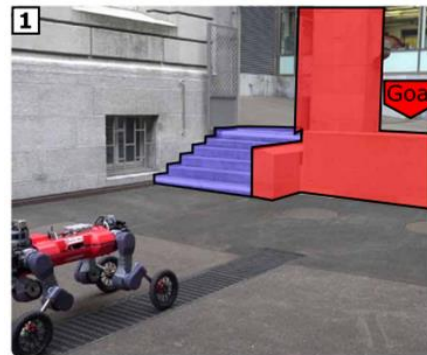
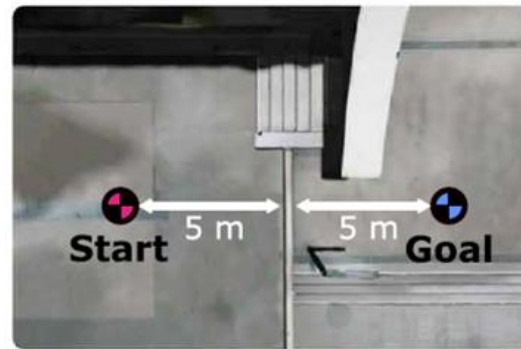


Figure 4 displays four plots comparing the performance of 'Ours', 'Ours without memory', and 'Baseline' across four metrics. The legend indicates: Ours (blue), Ours without memory (purple), and Baseline (pink).

- i. Failure rate:** A bar chart showing failure rate (%). 'Ours' has a failure rate of 30, 'Ours without memory' has 80, and 'Baseline' has 50. An orange arrow points down with the text 'Better'.
- ii. Collision rate:** A bar chart showing collision rate (%). 'Ours' and 'Ours without memory' have a collision rate of 0, while 'Baseline' has 100.
- iii. Planning time:** A box plot showing time (s) on a logarithmic scale. 'Ours' has a mean time of 0.34 ms, while 'Baseline' has a mean time around 1.2 s.
- iv. Tracking error distribution:** Two histograms showing the density of tracking error (m/s). 'Ours' shows a distribution concentrated near 0.0 m/s, while 'Baseline' shows a distribution with peaks near 0.0 m/s and 1.0 m/s.

Cited by 12 articles:

- Department of Computer Science, The University of Texas at Austin, USA
- Department of Computer Science, The University of Virginia, USA
- University at Buffalo, USA
- Pennsylvania State University, USA
- Carnegie Mellon University, USA
- ETH Zürich, Switzerland
- Purdue University, USA
- DisneyResearchStudios, Switzerland
- Technical University of Munich, Germany
- Google DeepMind, USA
- The AI Institute, USA
- University of British Columbia, Canada
- Neuromeka, Korea
- Georgia Institute of Technology, USA
- Hong Kong University of Science and Technology
- Institute of Artificial Intelligence (TeleAI), China Telecom
- Shanghai University, China

Pros & Cons

Pros	Cons
▪ Speed on flat terrain AND agility on stairs ▪ Successful testing on real hardware	▪ Number of actuators

Possible exam questions

Question 1: What challenges do a wheeled-legged robots face in urban navigation and how does the hybrid locomotion controller in this article address these challenges?

Answer: Wheeled-legged robots must handle varied terrains and obstacles like stairs, uneven surfaces and dynamic obstacles in urban environments.

It uses model-free reinforcement learning to adapt gaits and transitions between walking and driving modes. This ensures a robust navigation across complex terrains and efficient operation at high speeds.

Question 2: Describe the hierarchical reinforcement learning framework used in this article for navigation and its role in autonomous urban missions.

Answer: The HRL framework includes a high-level controller for navigation and a low-level controller for locomotion, both trained through reinforcement learning.

The high-level controller computes velocity targets, while the low-level controller executes joint position and wheel velocity commands. This HRL system enables the robot to efficiently navigate and adapt to obstacles autonomously over kilometer-scale urban missions.

A red three-wheeled robot, resembling a Pioneer 3 mobile base, is positioned in a narrow hallway. The robot has a red body, black wheels, and various sensors and components mounted on top. It is facing towards the right side of the frame. To the left of the robot is a staircase with a metal railing. In the background, there is a doorway leading to another room, with a green exit sign above it. The floor is made of large, light-colored tiles. The walls are a neutral, light color.

B. Narrow space