

Legged Robots @ ETH

EPFL, 2024

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ETH Zurich and ANYbotics AG
29.10.2024



Mobile Robots that can go ANYwhere
to take over the dirty and dangerous jobs



Research areas at RSL

- Focus: Locomotion and mobile manipulation with uncertain/unstructured environments
 - **Design** of actuators and robots
 - Model-based **planning and control** for hybrid systems
 - **Reinforcement learning** with sim-to-real transfer
 - Multi-modal **perception** and classification for traversability estimation and **navigation**

Facts & Figures

- 6 PostDocs
- 25 PhD students
- 25 engineering/staff

- Different platforms

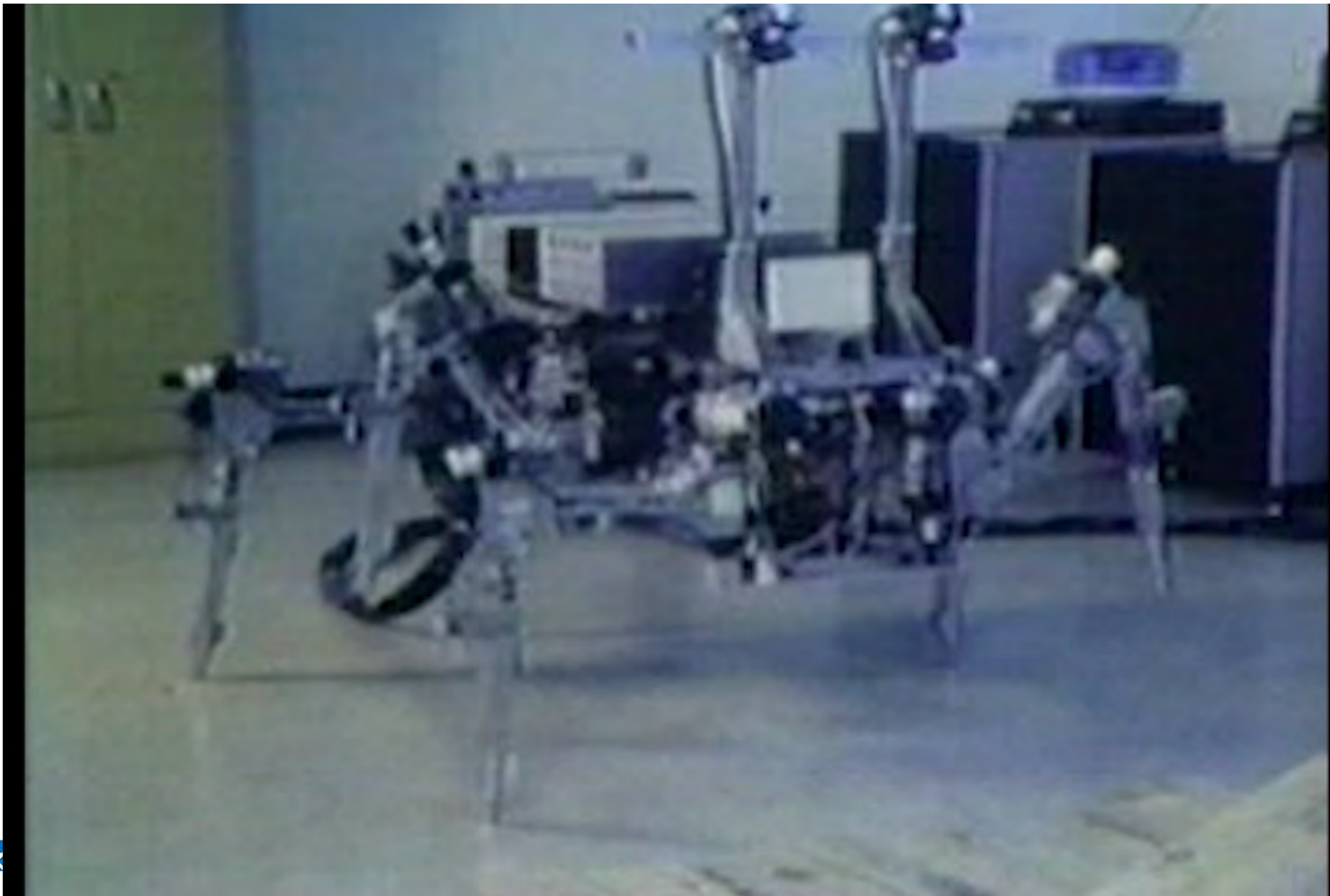


Lecture today in 5 parts

1. Quadrupeds
2. Control
3. Navigation
4. Applications
5. (if time) Future stuff

Part 1: RSL Quadrupeds

OSU walker, early 80ies



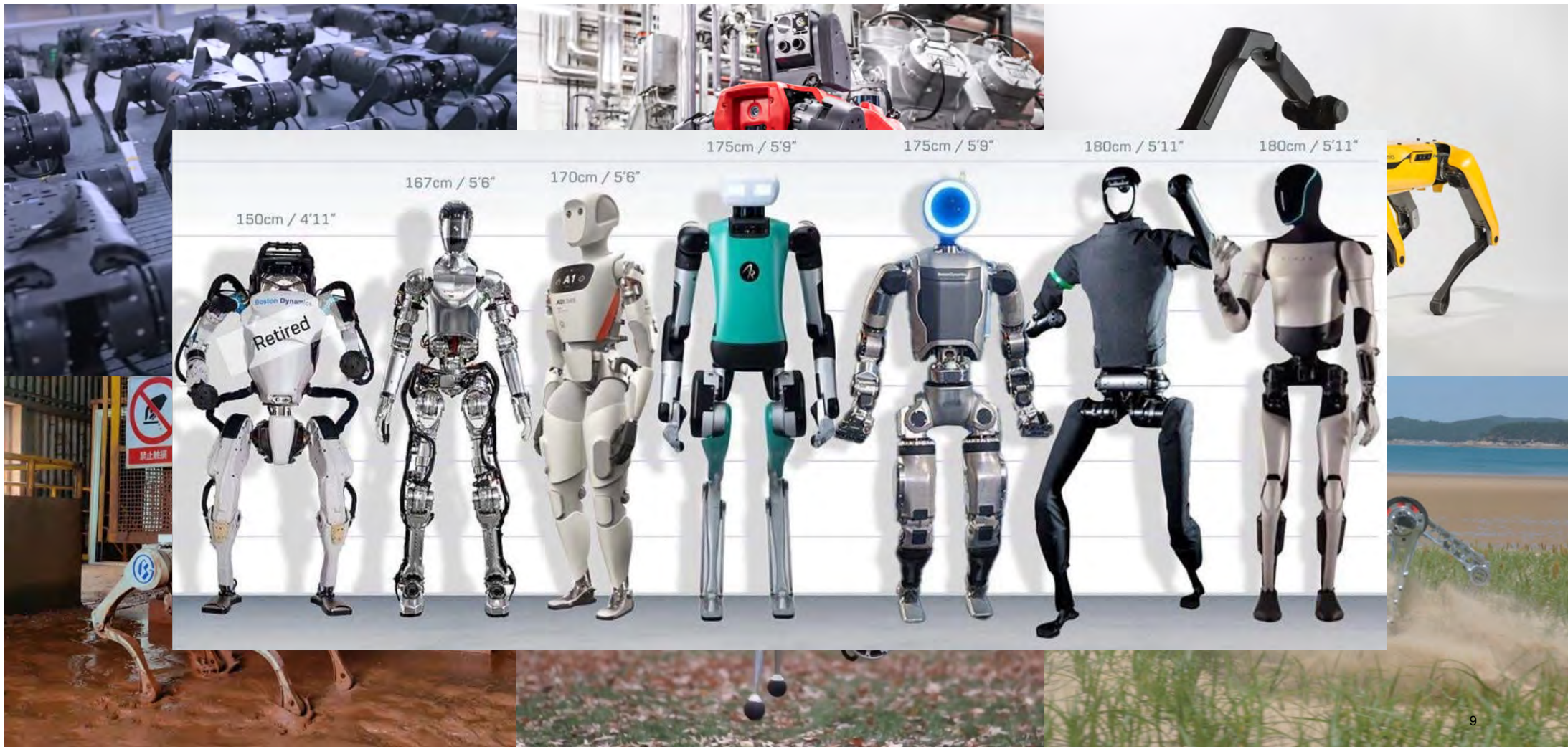
Raibert, Leg Lab, late 80ies





Boston Dynamics

Legged (Quadruped) robots have become a commodity



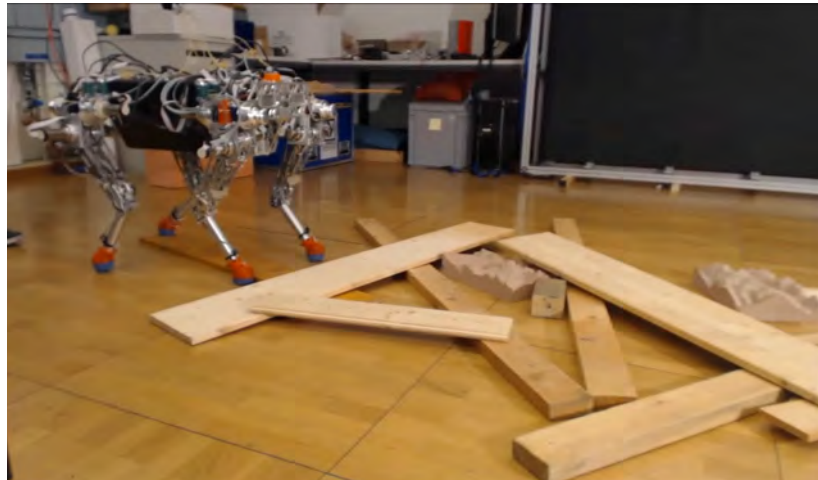
From research prototypes to commercial products in 1 decade



2012

ETH Zurich - Robotic Systems Lab

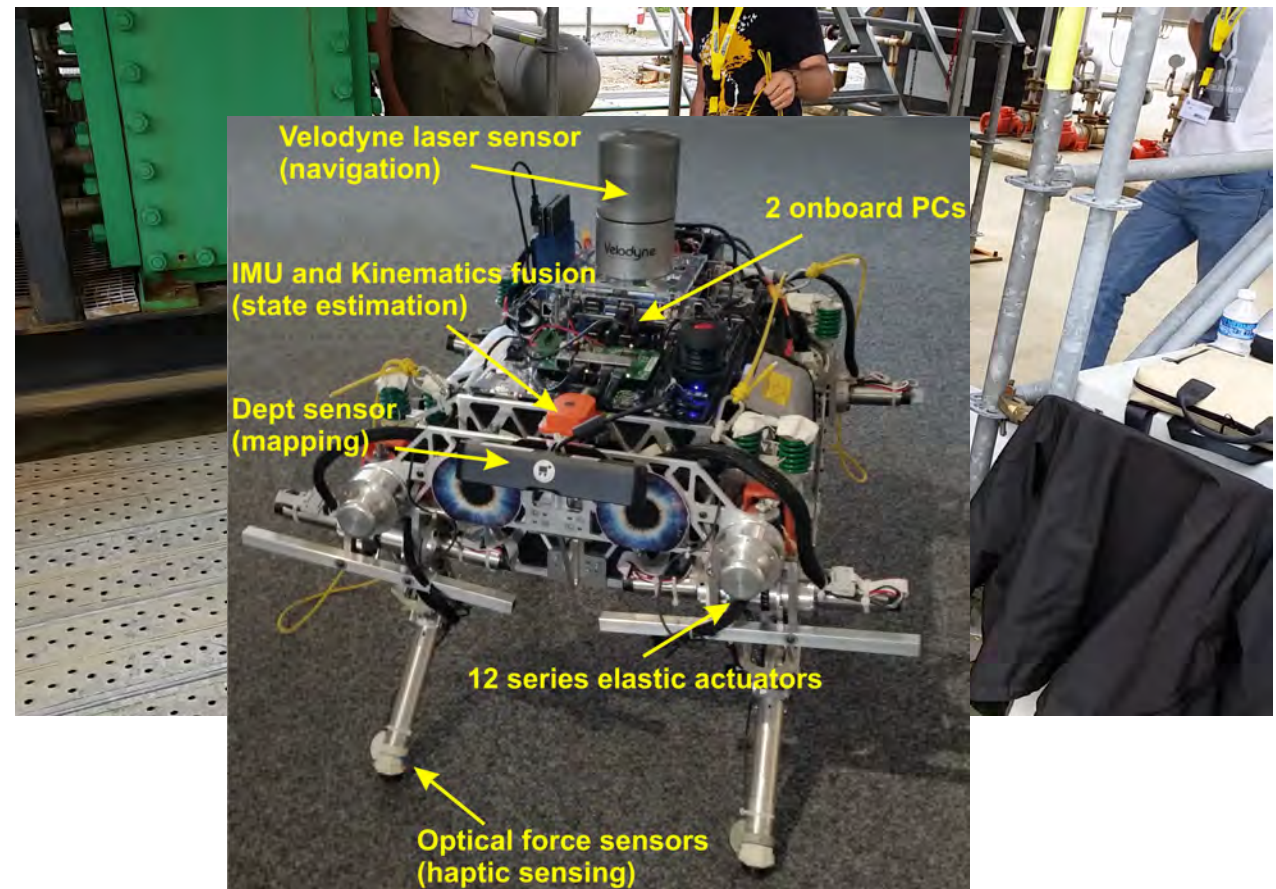
Research on autonomous robots



18.10.2022

ARGOS – first field application of legged robots towards industrial inspection

- ARGOS competition 2013-2017
- 4 teams with classic tracked vehicles
- 1 team with a legged robot



From research prototypes to commercial products in 1 decade

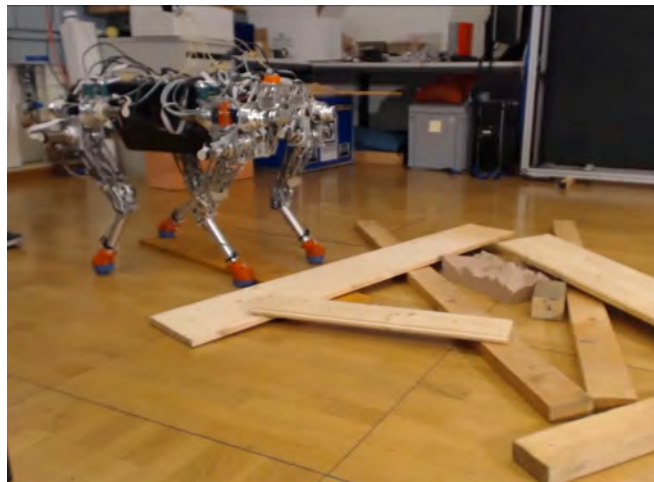


ETH Zurich - Robotic Systems Lab

Research on autonomous robots

ANYbotics

founded 2016, >150 employees



From research prototypes to commercial products in 1 decade



ETH Zurich - Robotic Systems Lab

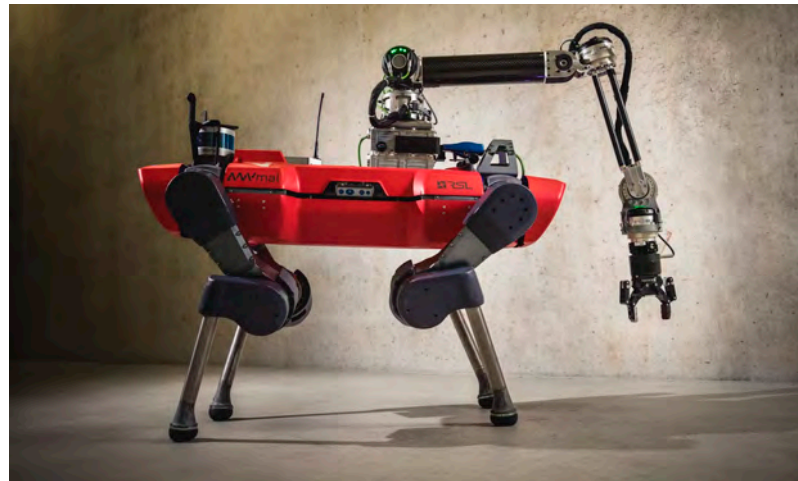
Research on autonomous robots

ANYbotics

founded 2016, >150 employees



ETH zürich RSL
Robotic Systems Lab



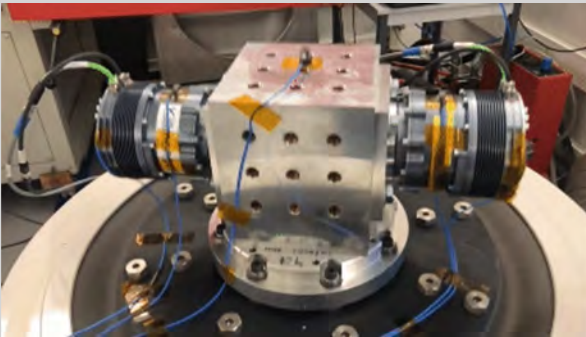
Specifications

- Integrated, torque controllable and impact robust joint units
- Simple 3-link kinematic leg structure
- Mainbody with 2-3 PCs
- Perception sensors for autonomy
 - Velodyne lidar
 - 6 RGB-D
 - 2 wide-angle RGB
- Inspection Payload
 - Zoom camera
 - Thermal camera
 - Light
 - Microphone



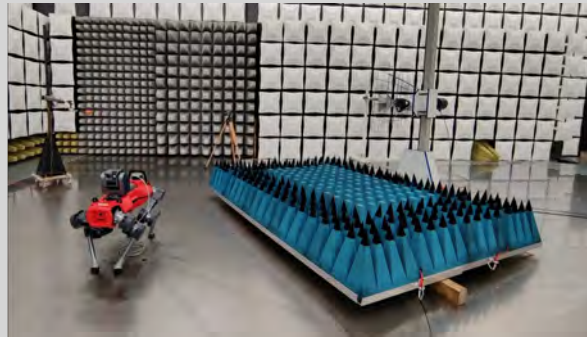
ANYmal D

Design for reliability



Reliability

Large operating temperature ranges,
thermal cycling, humidity
exposure/cycling, vibration/shock,
component lifetimes



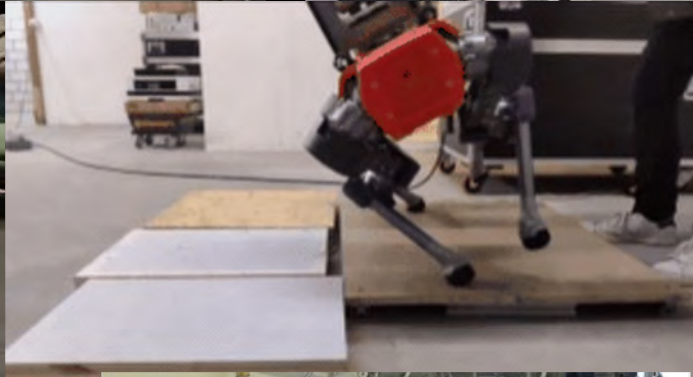
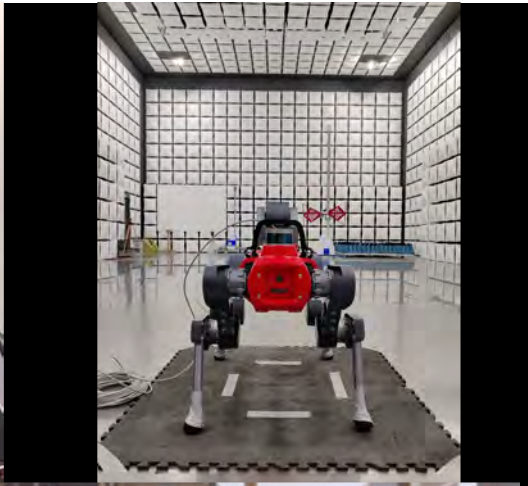
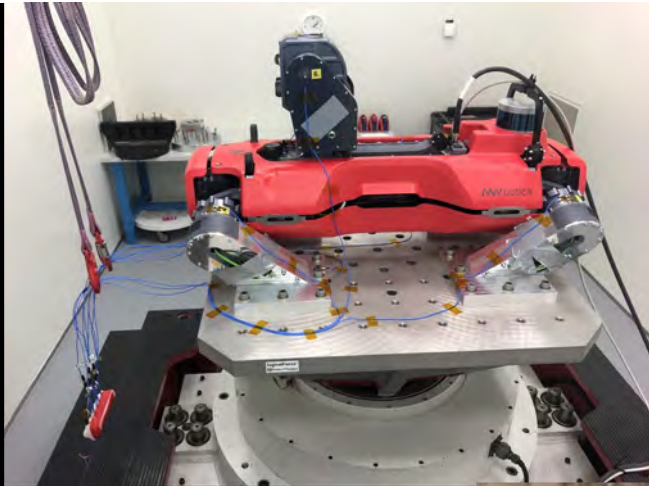
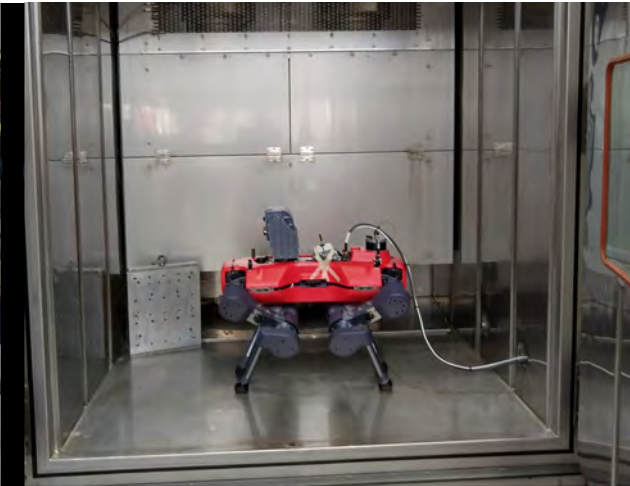
Electromagnetic & radio compliance

Emissions, immunity, electrostatic
discharge, radios



Environment

Water/dust ingress, UV radiation, corrosion,
humidity/condensation

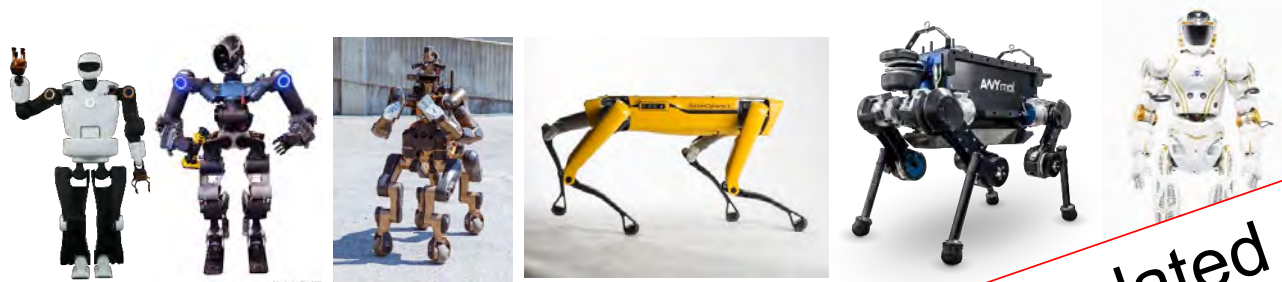




Part 2: Control

State of the Art Legged Robots – and their actuation

1. High-gear system with elasticity or torque sensor



2. Low gear system with current control only

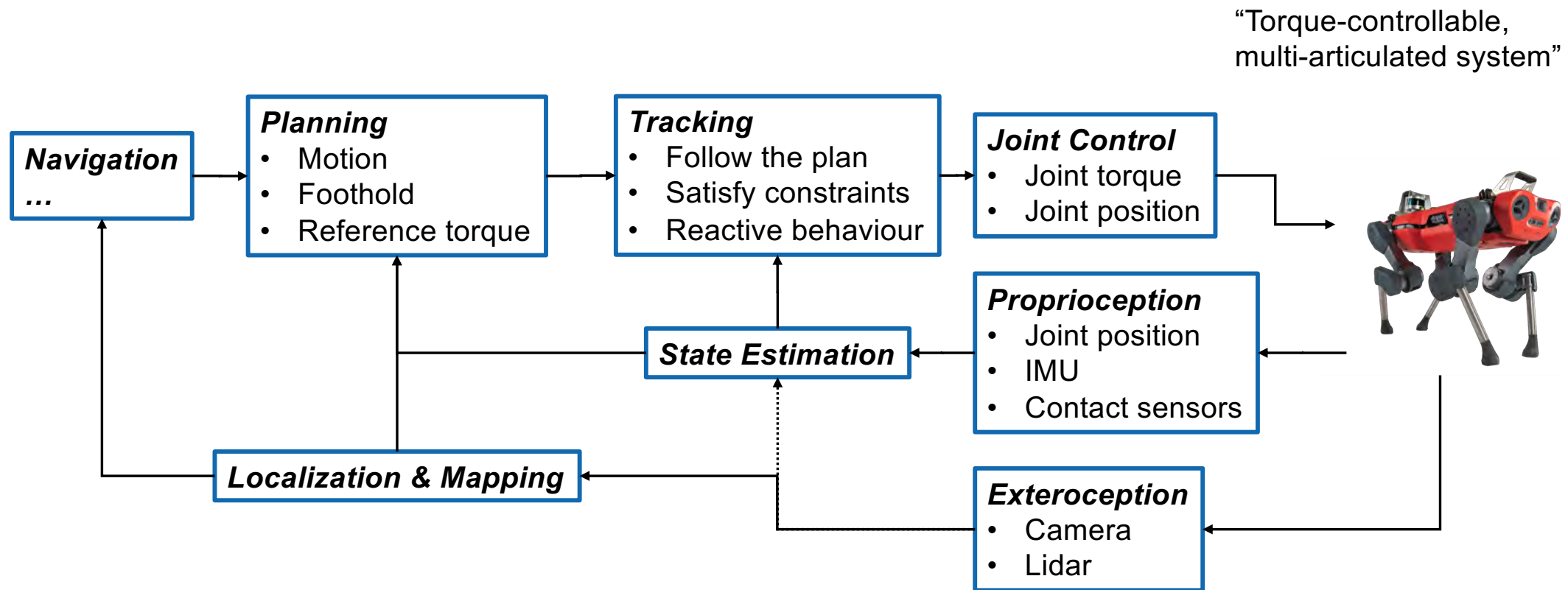


3. Hydraulic (pressure and/or load cell)

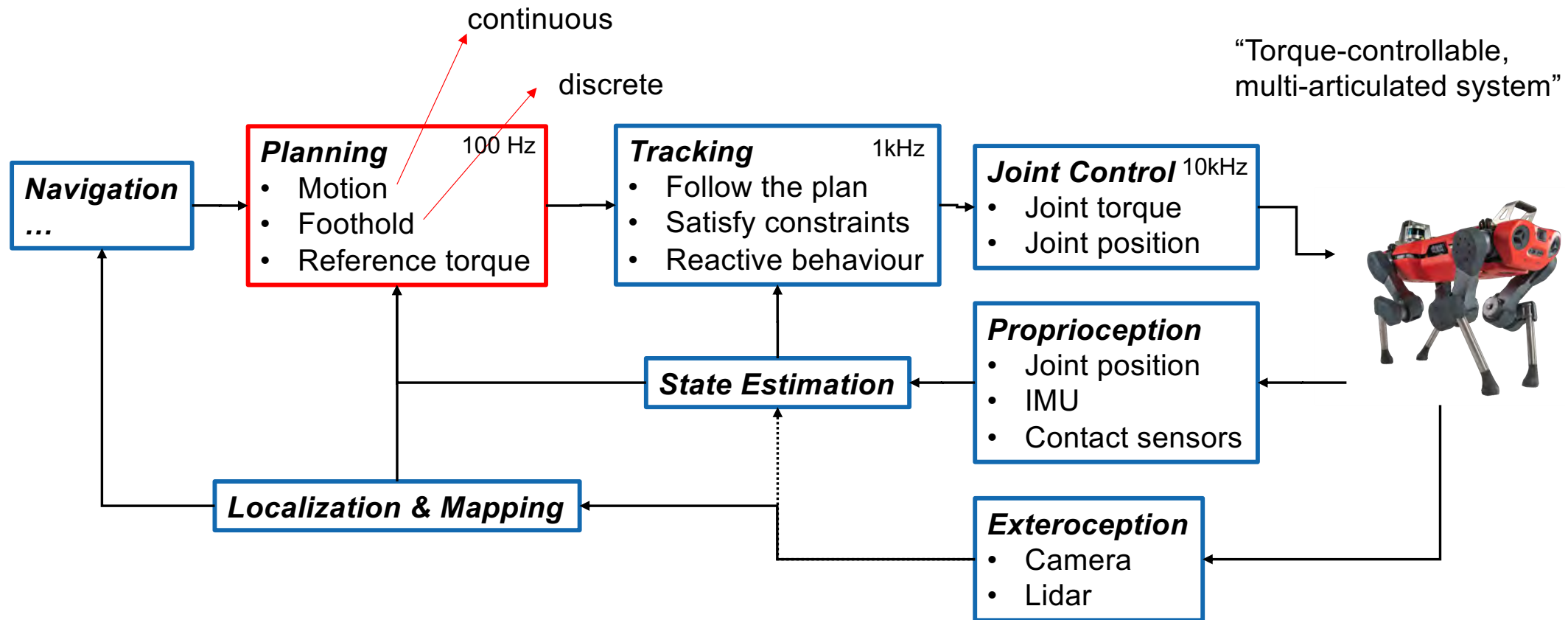


Torque-controllable, multi-articulated system"

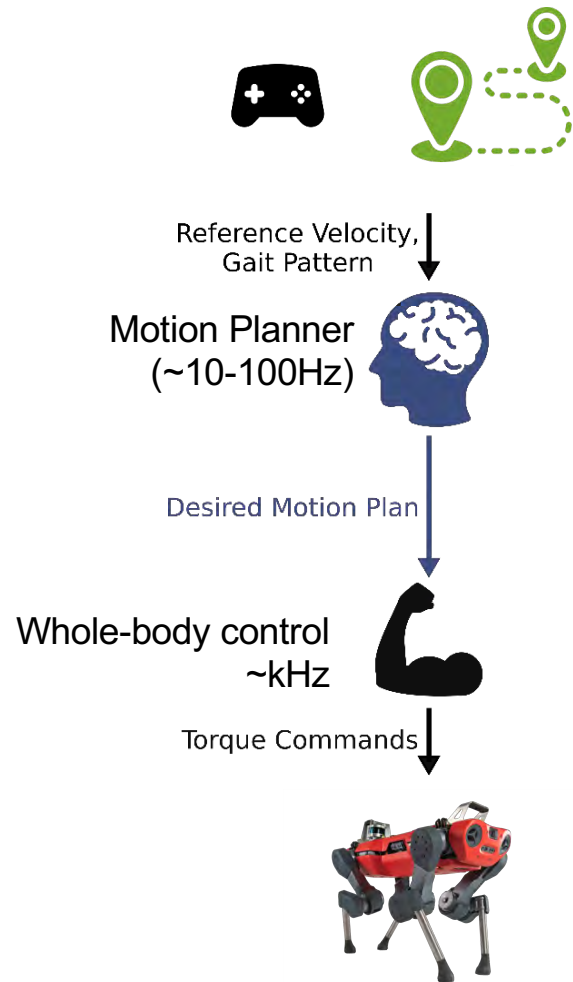
Control, Planning and Autonomy for Legged Robots



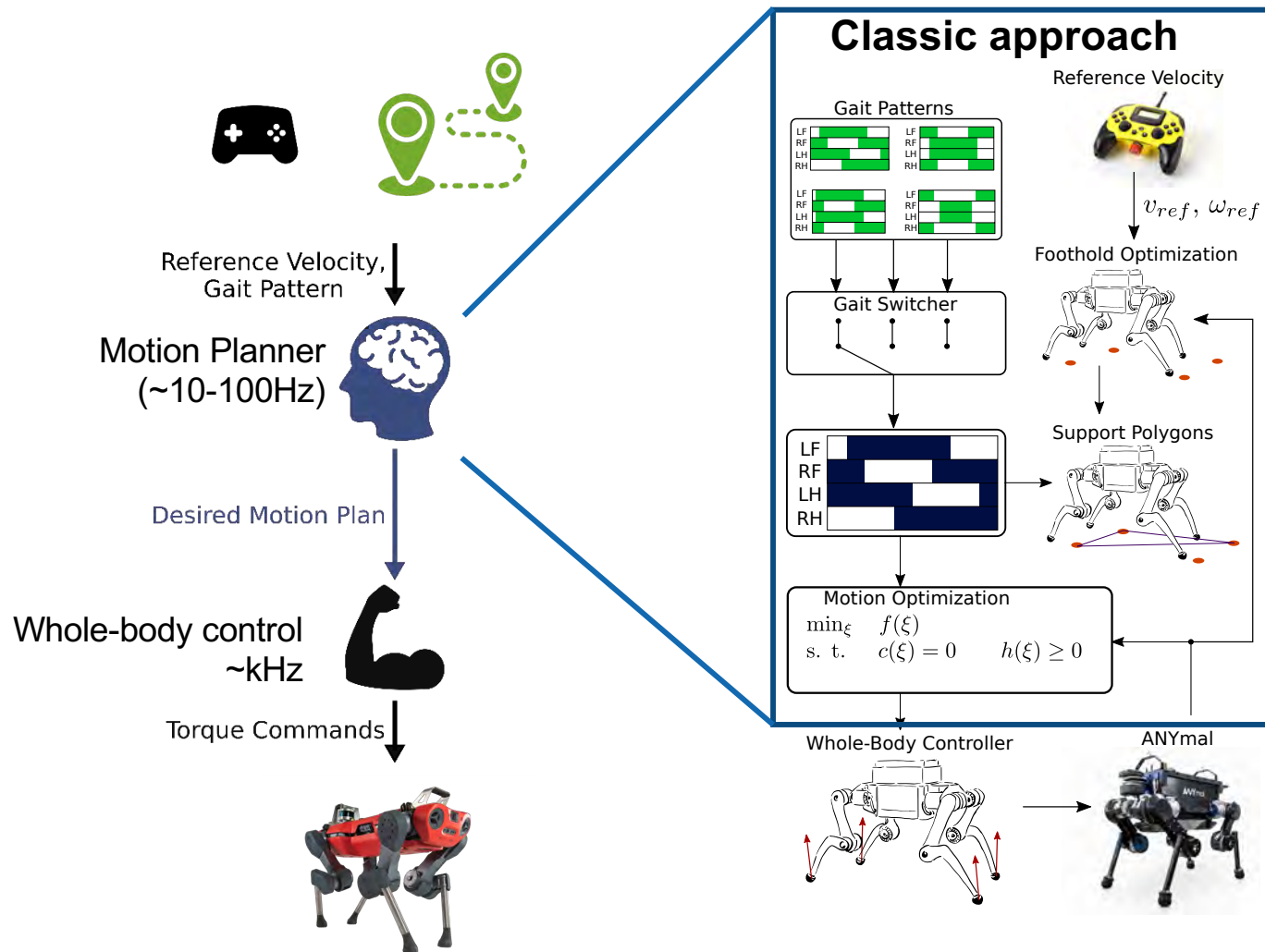
Control, Planning and Autonomy for Legged Robots



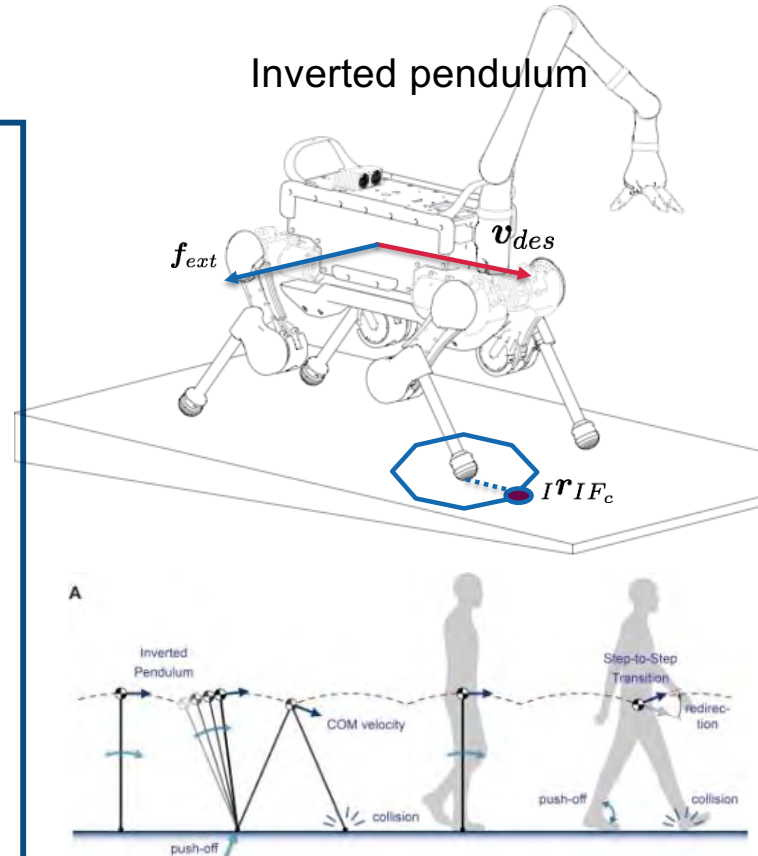
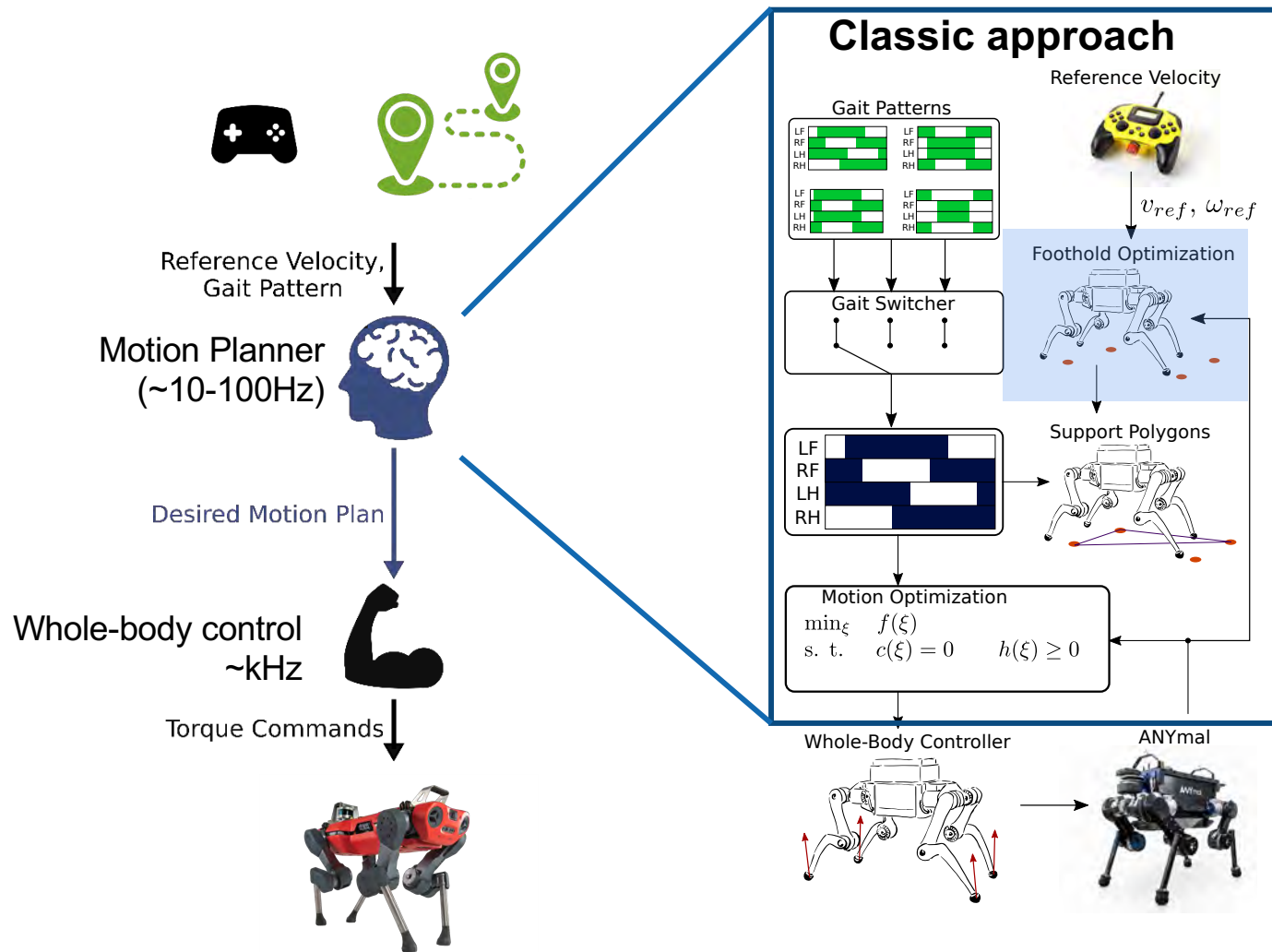
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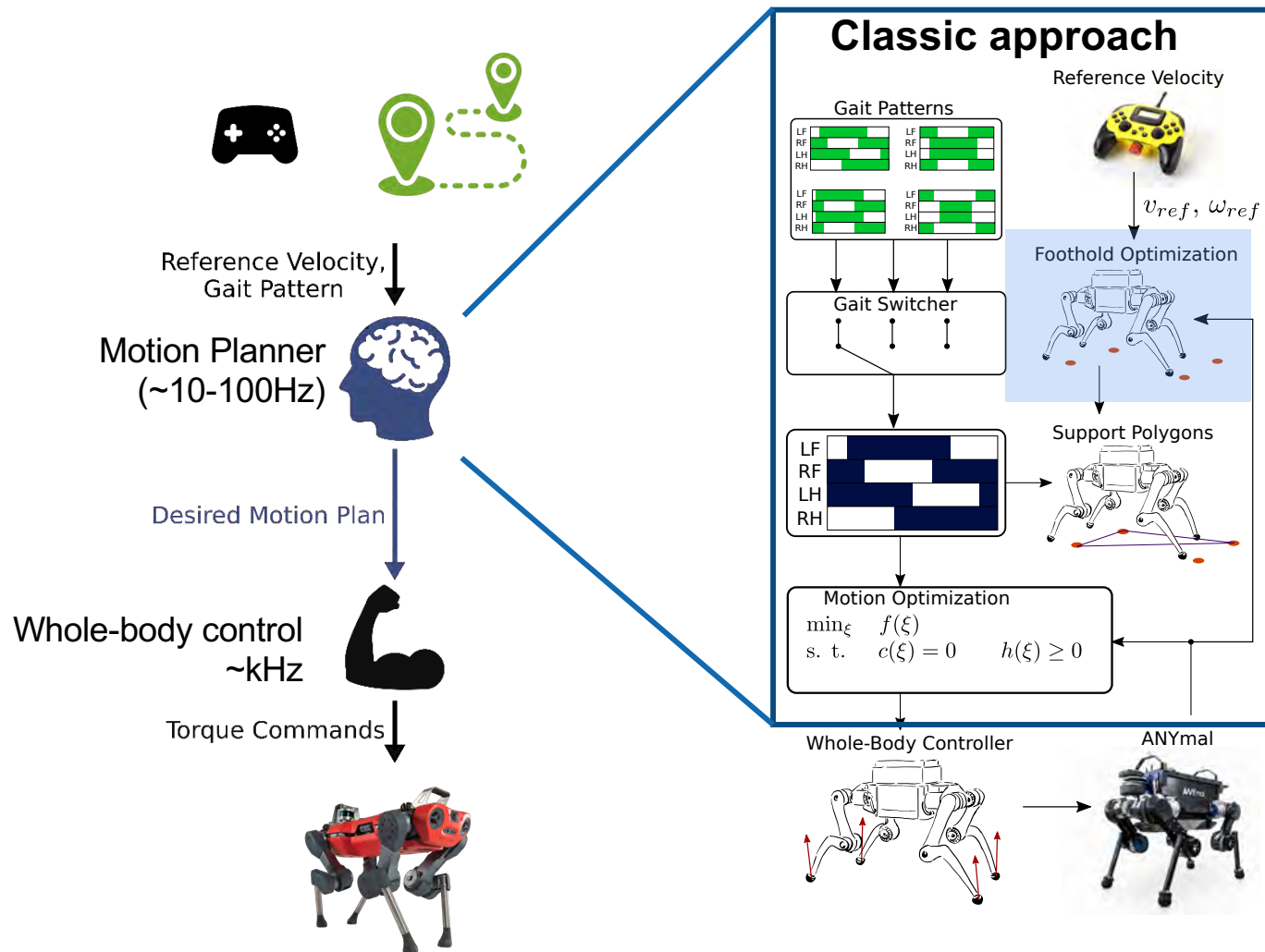
Control, Planning and Autonomy for Legged Robots



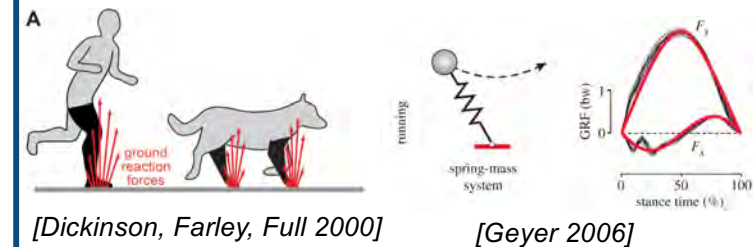
Control, Planning and Autonomy for Legged Robots



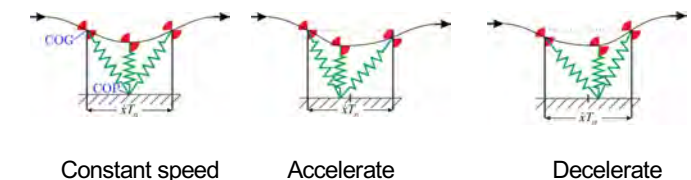
Control, Planning and Autonomy for Legged Robots



- Biomechanical studies suggest SLIP models to describe complex running behaviors



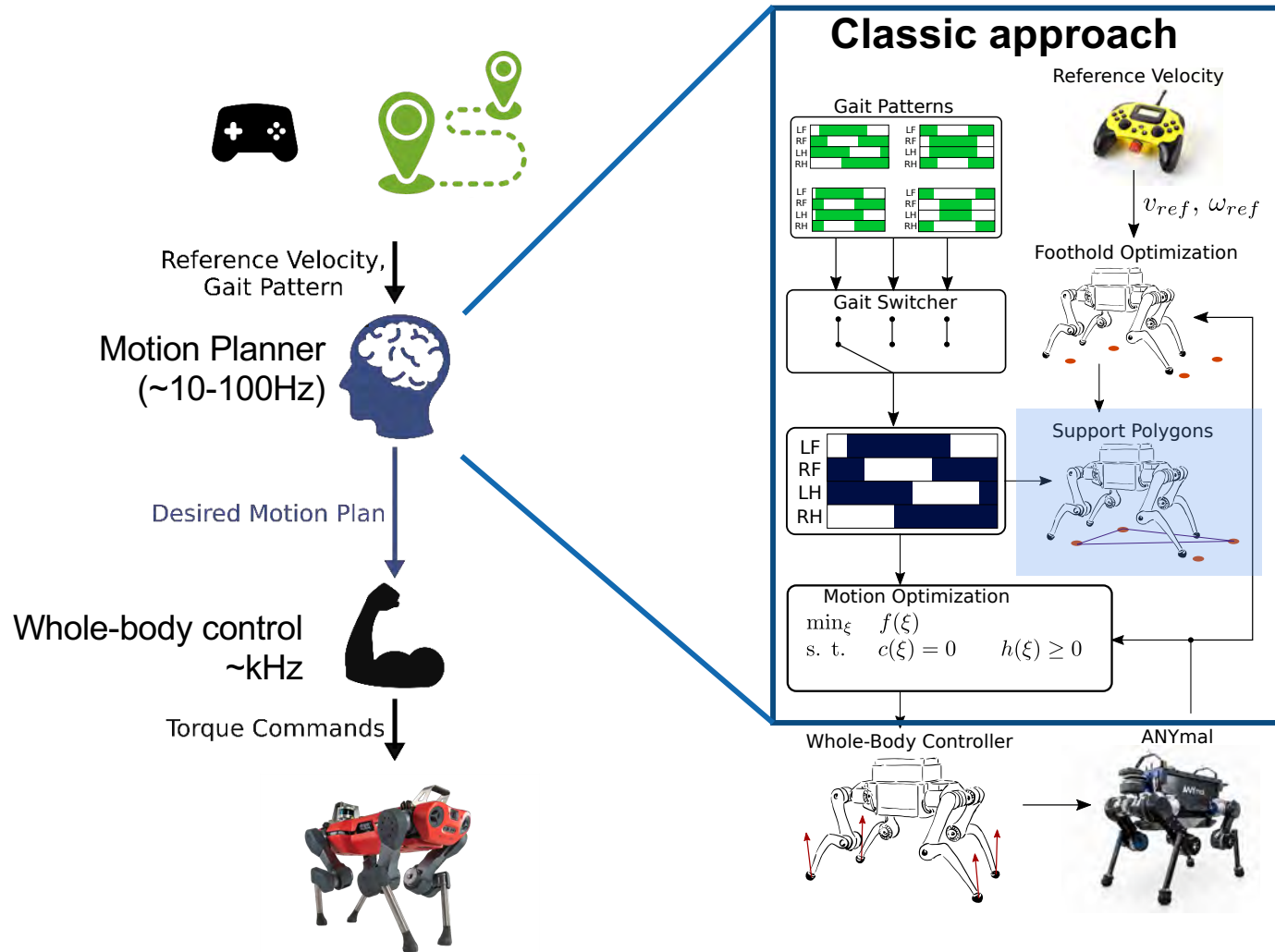
- Simple step-length rule to adjust the velocity



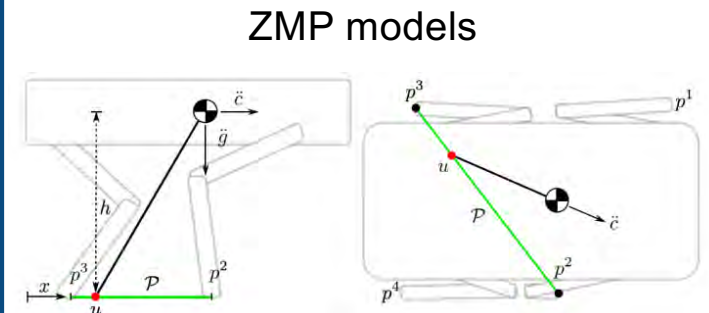
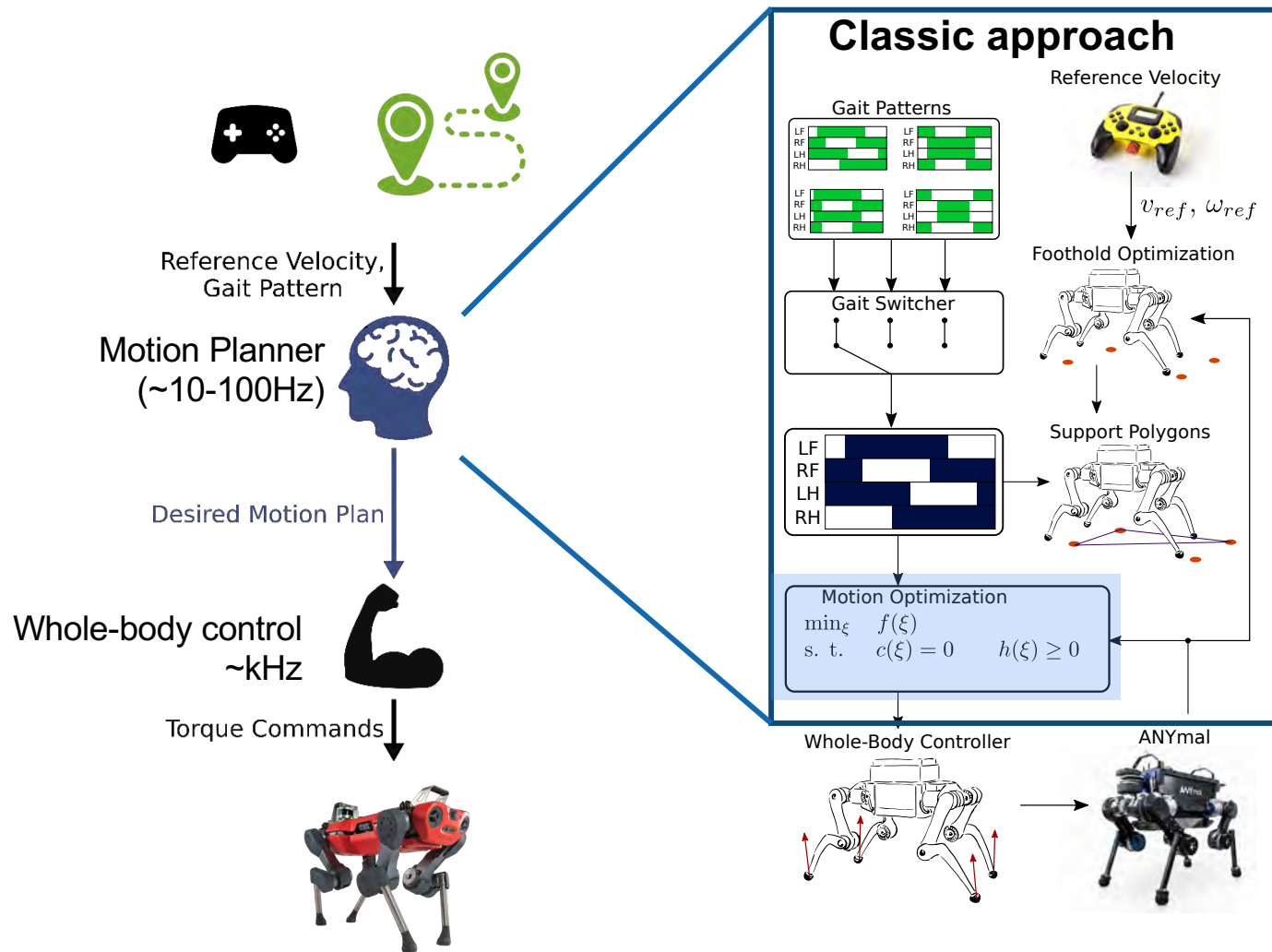
$$\mathbf{r}_F = \frac{1}{2} \dot{\mathbf{r}}_{HC,des} T_{st} + k_R^{FB} (\dot{\mathbf{r}}_{HC,des} - \dot{\mathbf{r}}_{HC}) \sqrt{h_{HC}}$$

[Raibert 1986]

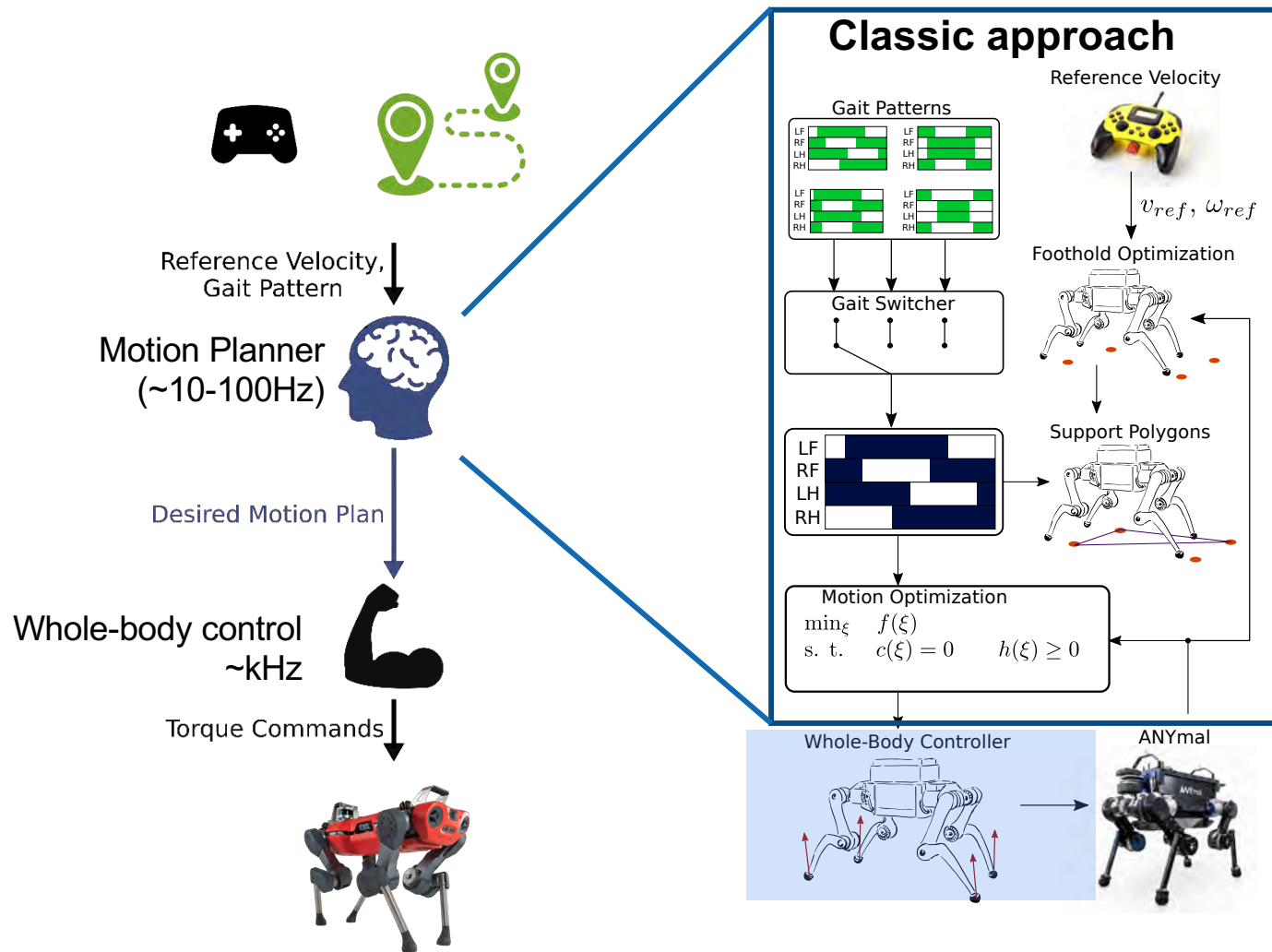
Control, Planning and Autonomy for Legged Robots



Control, Planning and Autonomy for Legged Robots



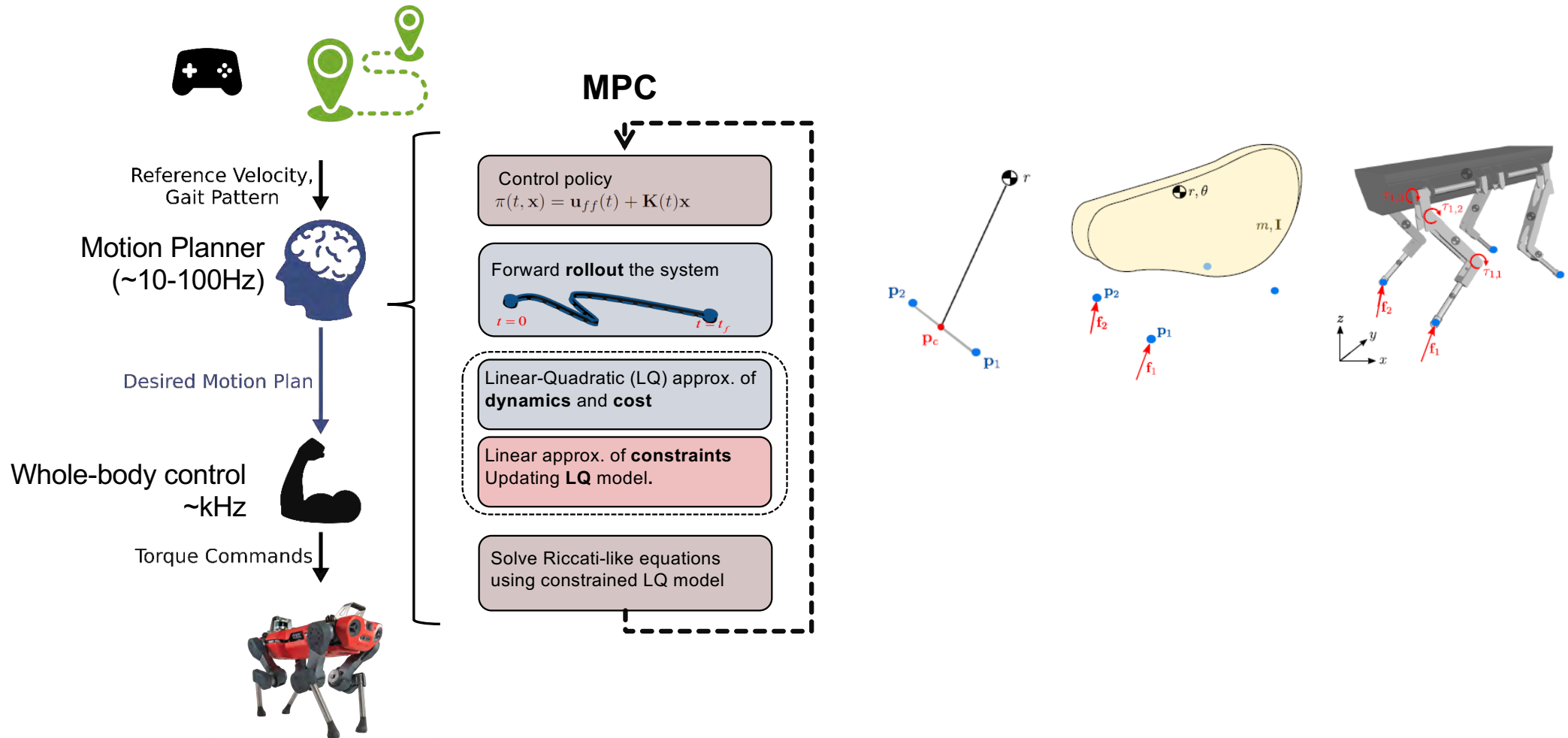
Control, Planning and Autonomy for Legged Robots



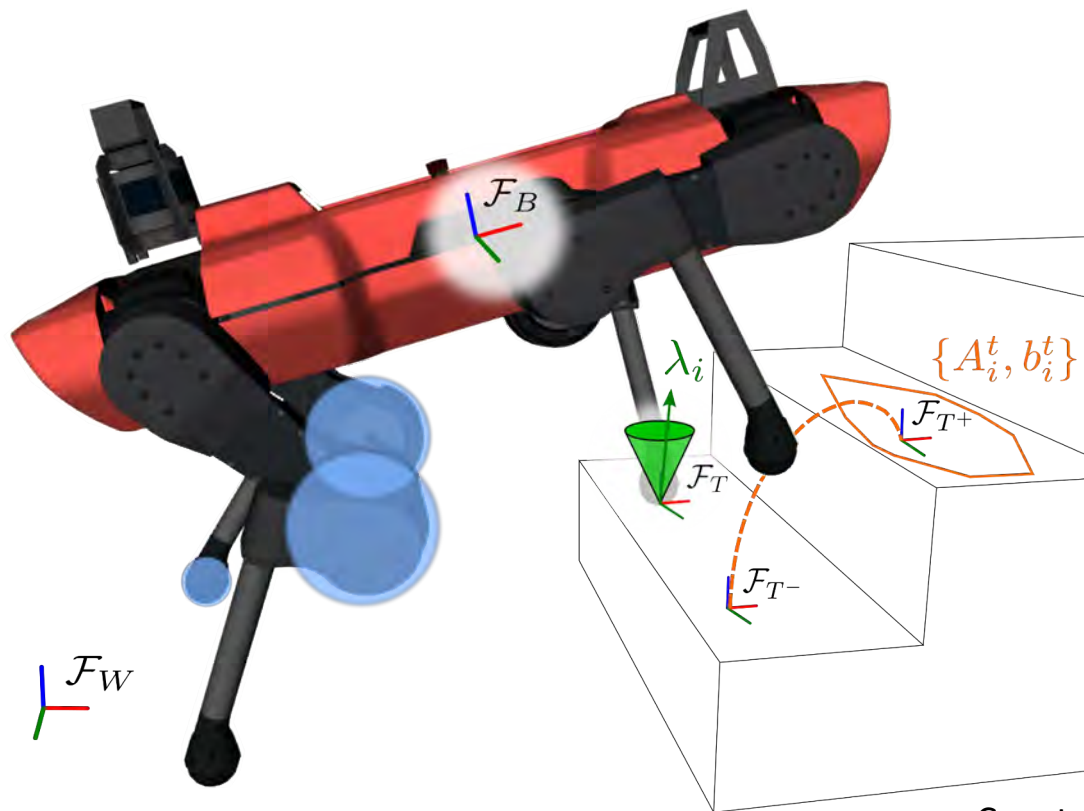
- Solves a cascade of prioritized tasks
 - Equation of motion
 - No slippage condition
 - Limits on torques
 - Motion tracking
 - ...



Control, Planning and Autonomy for Legged Robots



Locomotion as optimization problem



Finite-Time Optimal Control Problem

$$\begin{cases} \min_{\mathbf{u}(\cdot)} & \Phi(\mathbf{x}(T)) + \int_0^T L(\mathbf{x}(t), \mathbf{u}(t), t) dt \\ \text{s.t.} & \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t) \\ & \mathbf{g}_1(\mathbf{x}(t), \mathbf{u}(t), t) = 0 \\ & \mathbf{g}_2(\mathbf{x}(t), t) = 0 \\ & \mathbf{h}(\mathbf{x}(t), \mathbf{u}(t), t) \geq 0 \\ & \mathbf{x}(0) = \mathbf{x}_0, \end{cases}$$

Constrained DDP-based Algorithm (SLQ) [Farshidian 2017 IFAC]

[\[https://bitbucket.org/leggedrobotics/ocs2\]](https://bitbucket.org/leggedrobotics/ocs2)

Locomotion as optimization problem

Source: youtube, video by Boston Dynamics, Talk by Scott Kuindersma



Legged robots work well on structured ground
... but they often have issues over compliant, slippery or moving terrain

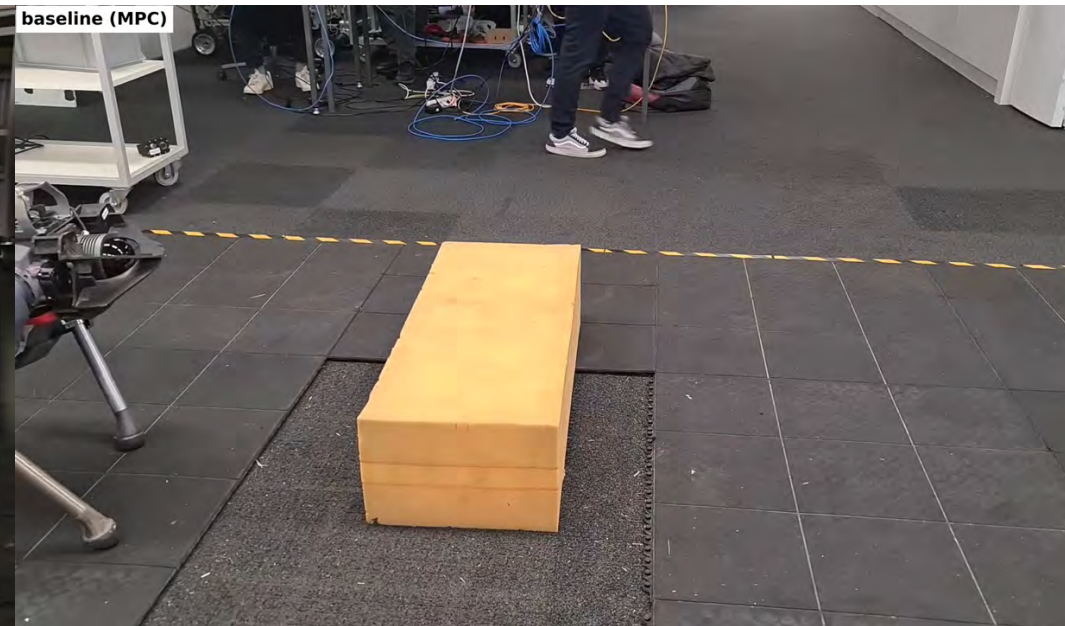
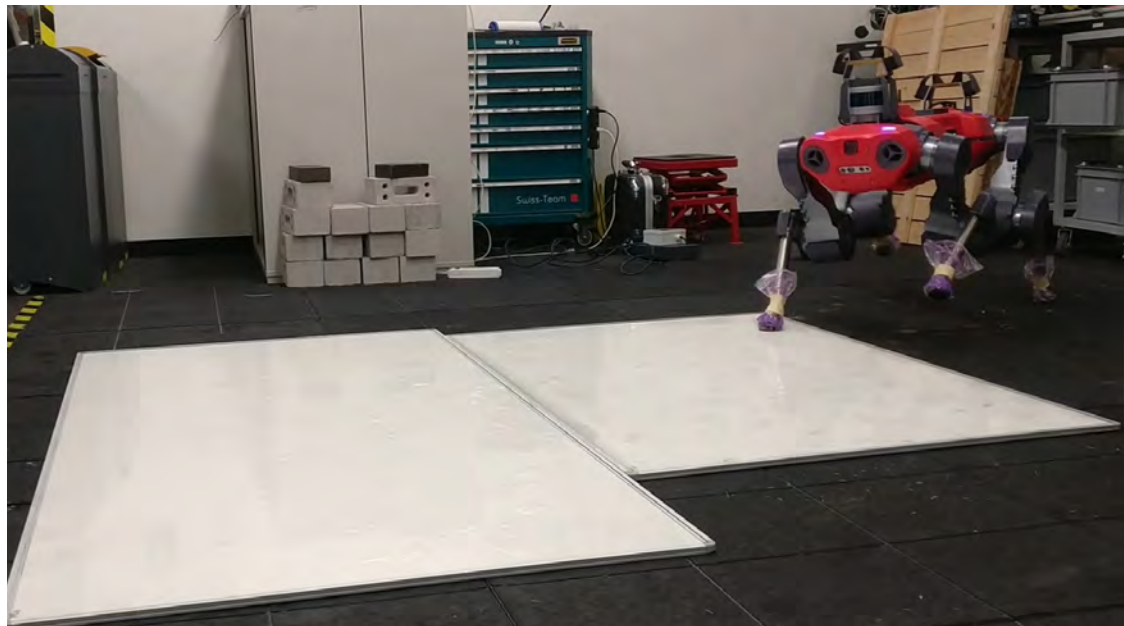
- **Corner cases of model-based controllers**
- Underlying assumptions:
 - Contact only occurs at the feet
 - The terrain is static (and planar)



- Lots of handcrafted heuristics to compensate
 - Online disturbance observer and reaction
 - Slip detection and

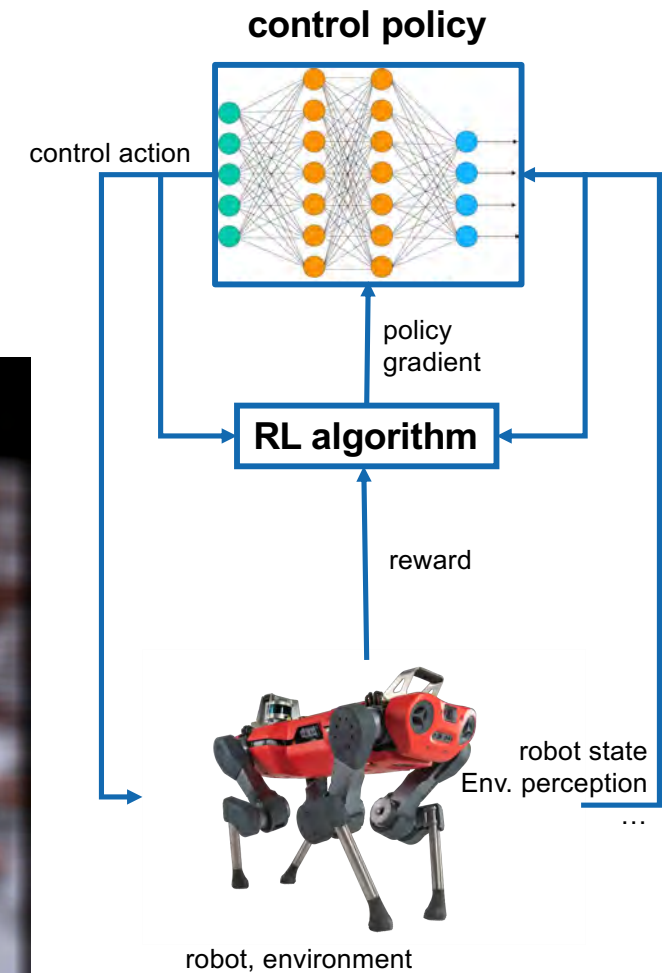
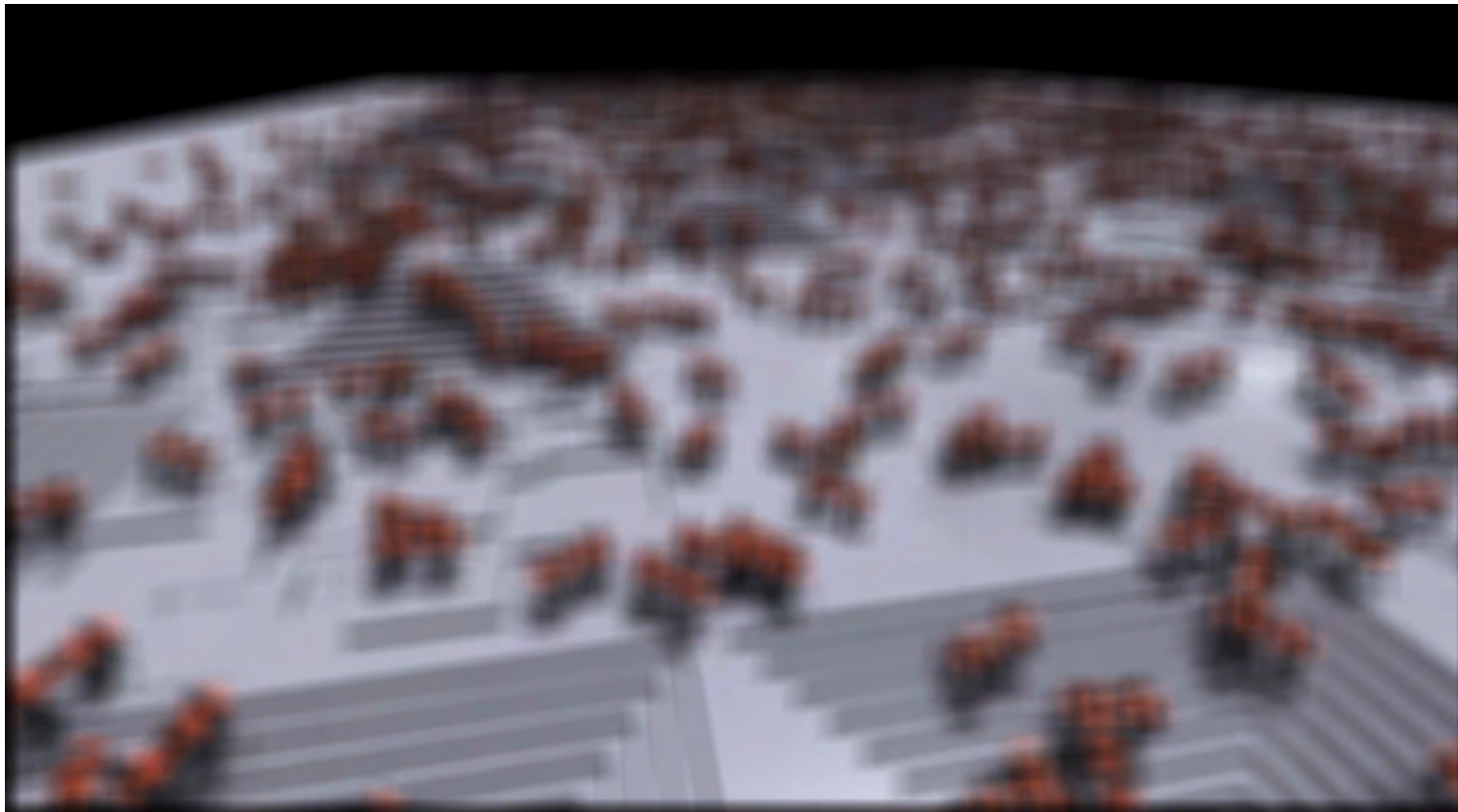
Could we not make the robot to learn all of this

- Gait and frequency adaptation
- Regain contacts...



Reinforcement learning for locomotion control

- Learn from massive data generated with a fast and accurate simulator

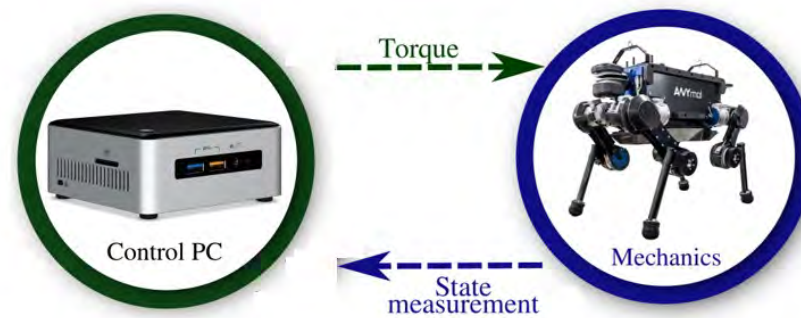


Deployment of learned policy on the robot

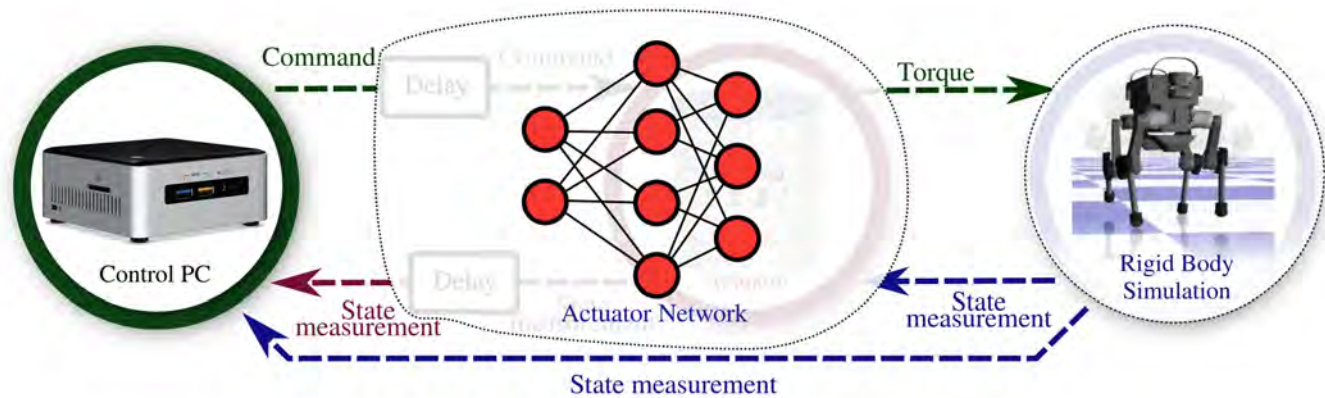
the reality gap



Sim-to-real: The reality gap



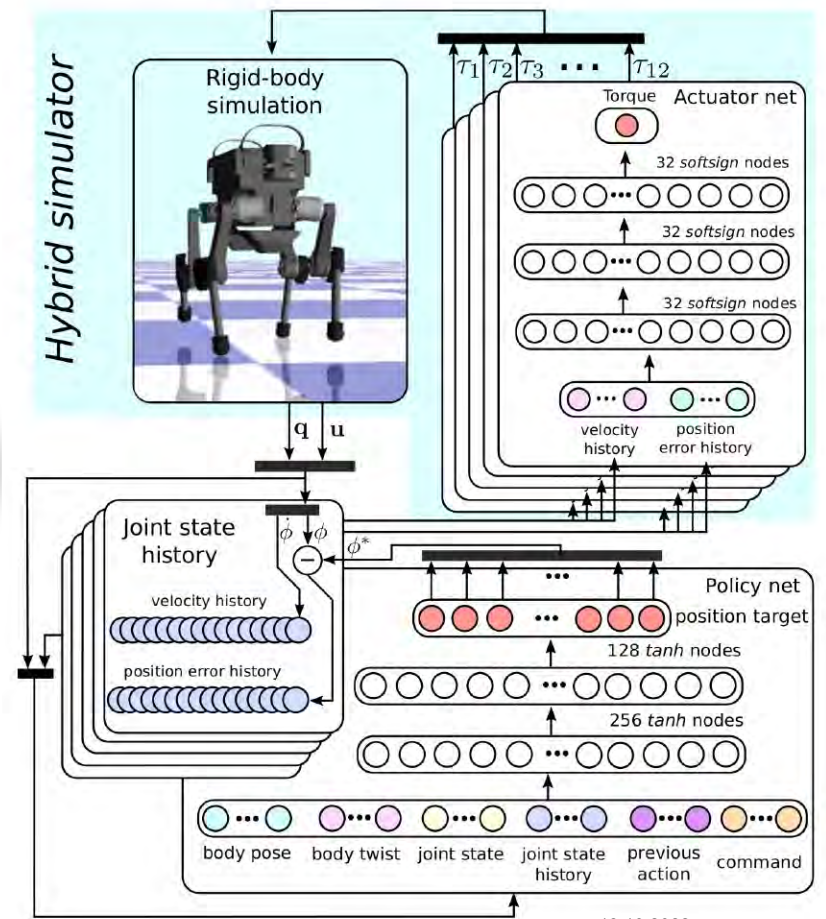
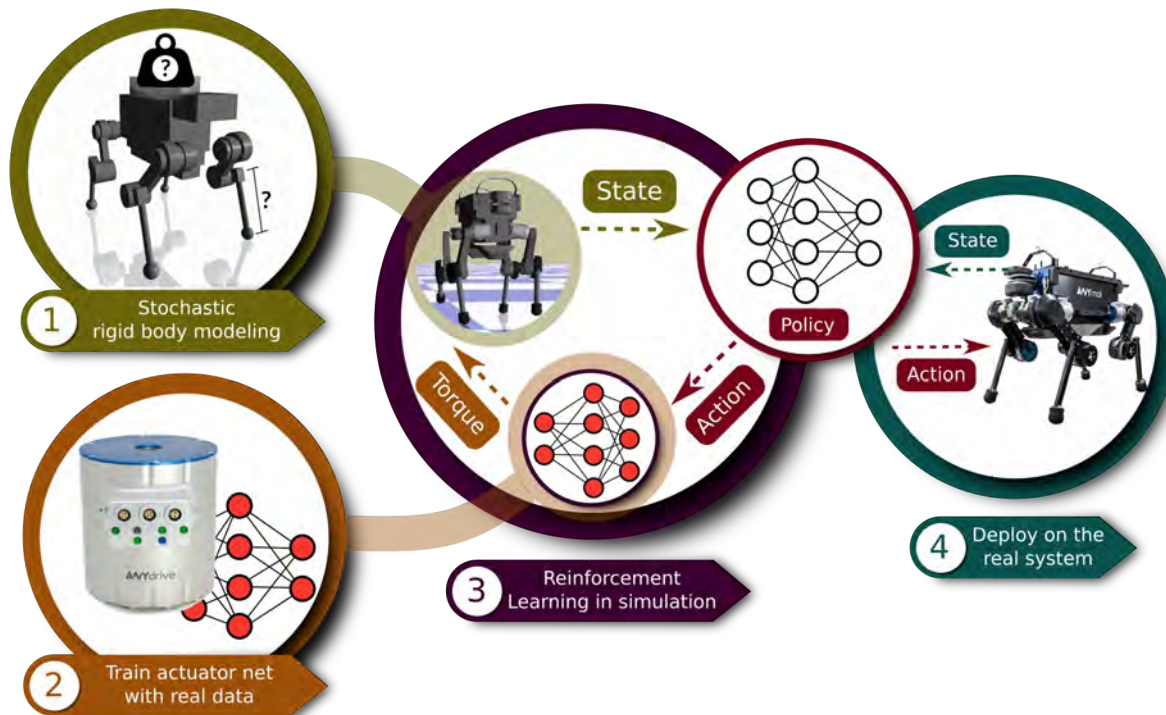
Sim-to-real: The reality gap



Difficult to model.
Easy to learn

Easy to model.
Difficult to learn

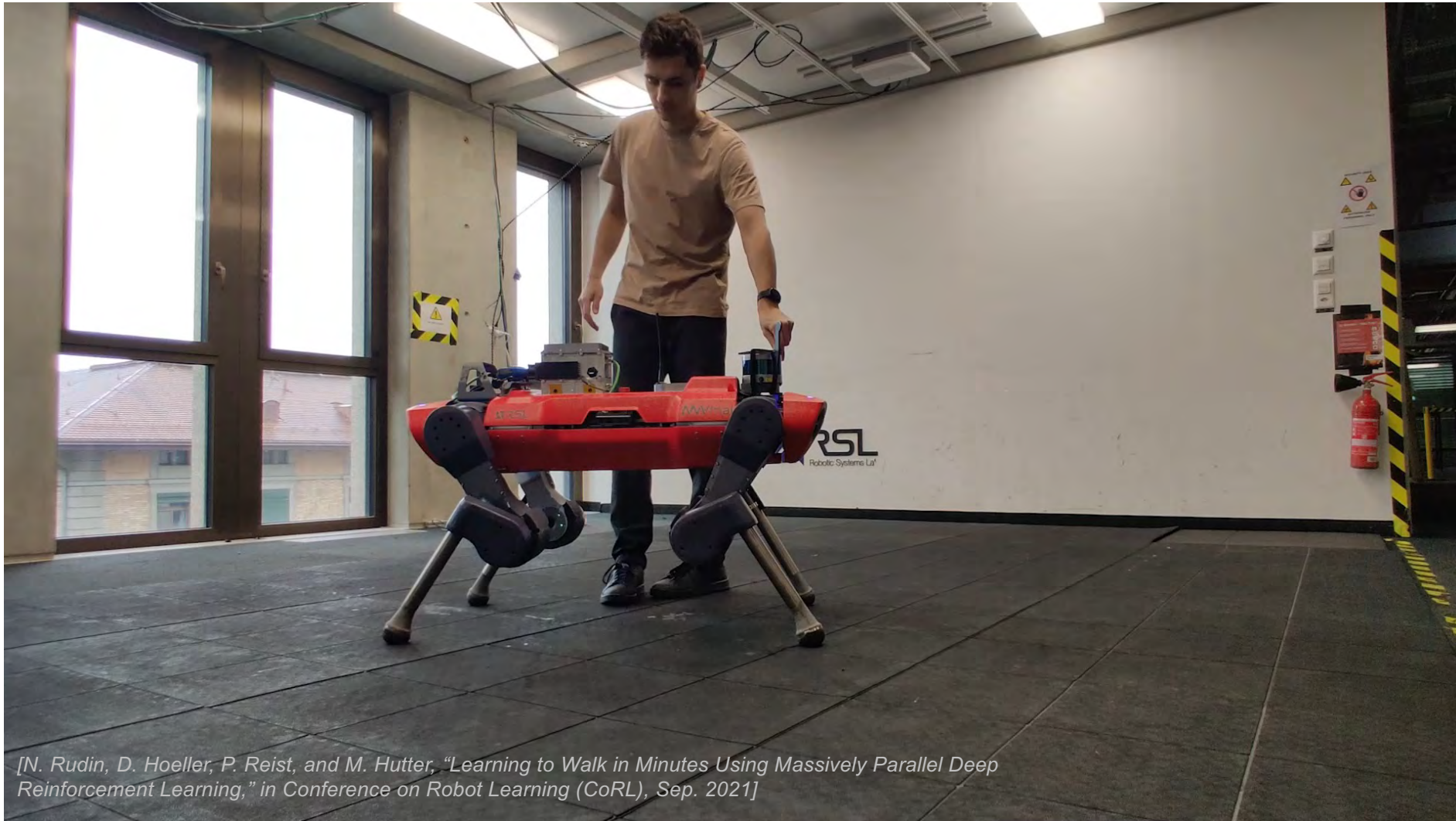
Simulation-based RL for legged robots



ANYmal is (one of) the first RL-controlled robot product

Every sequence:

- 15 policy iterations
- ~1.5M steps
- ~8.3 hours of simulated time

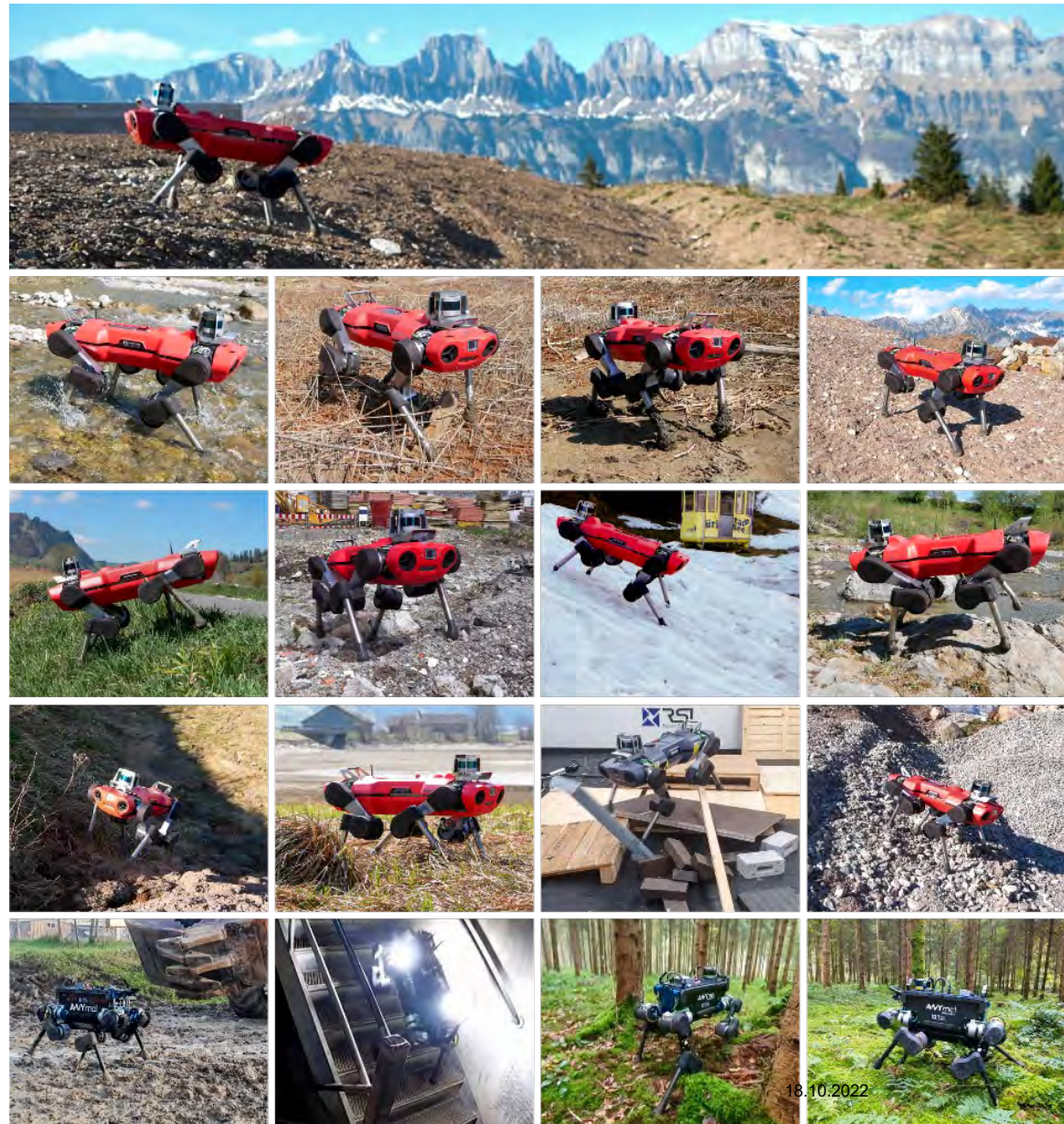


[N. Rudin, D. Hoeller, P. Reist, and M. Hutter, "Learning to Walk in Minutes Using Massively Parallel Deep Reinforcement Learning," in Conference on Robot Learning (CoRL), Sep. 2021]

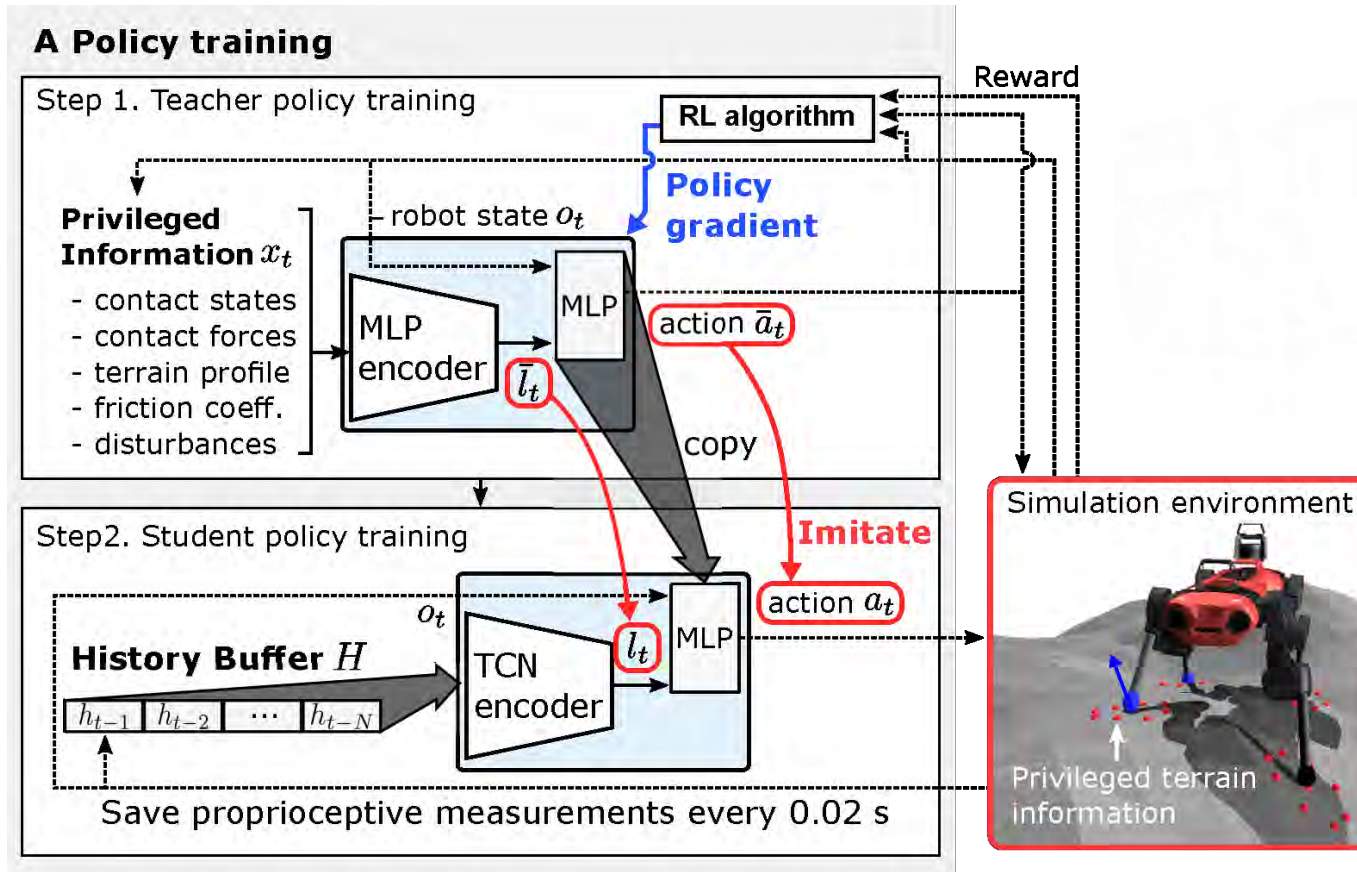
8.10.2022

Real World Deployment

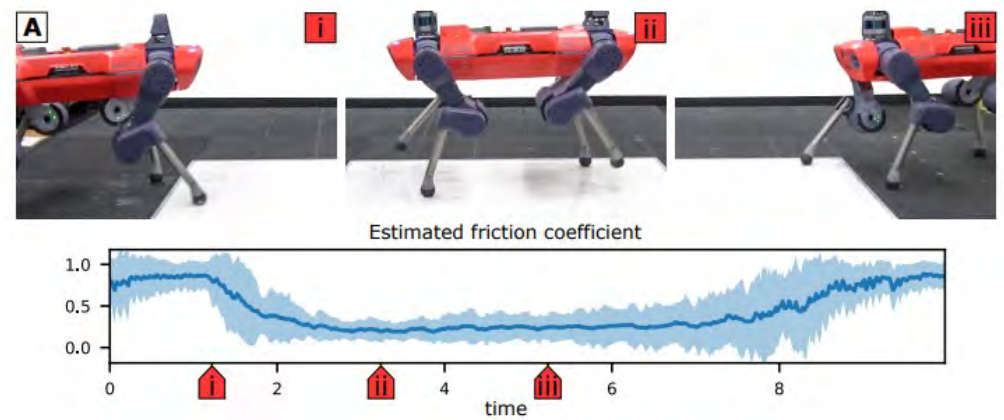
- Large variations in terrain in reality
 - Impossible to model in simulation
 - Hard to sense from perception
- What's important for locomotion



Method: privileged training

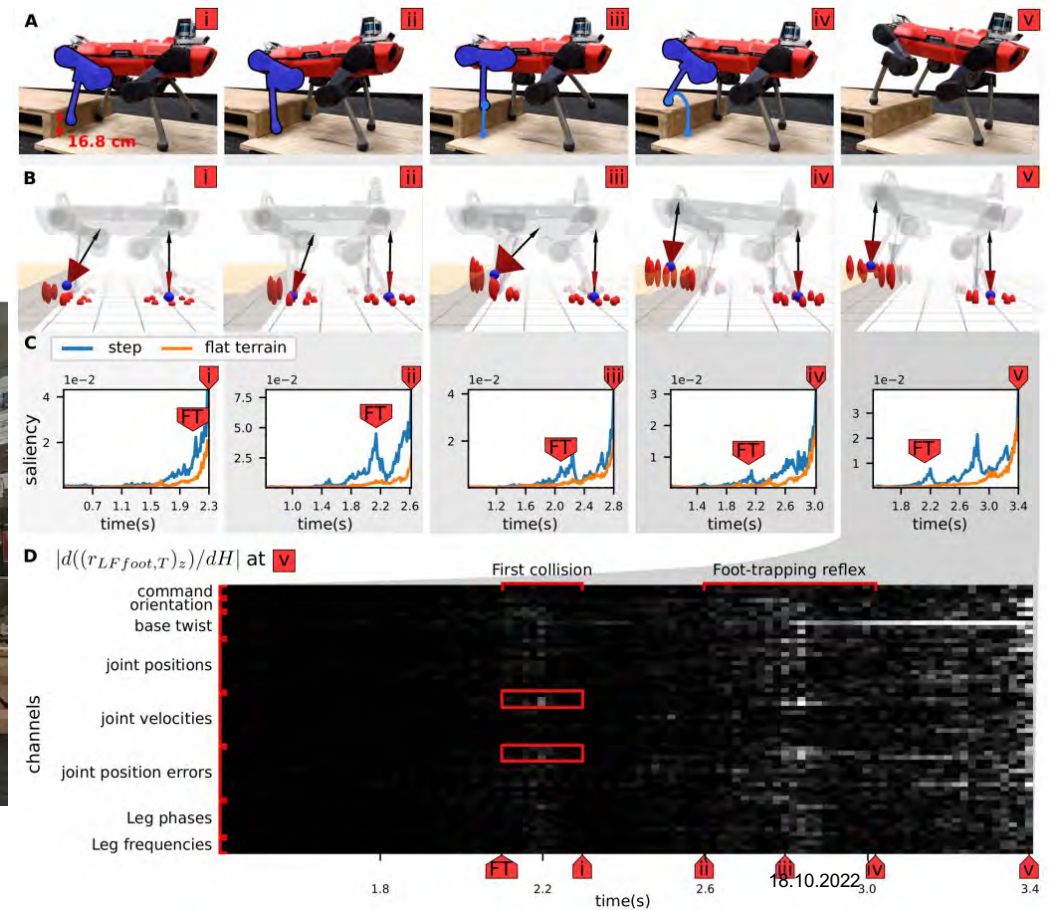


Friction estimation

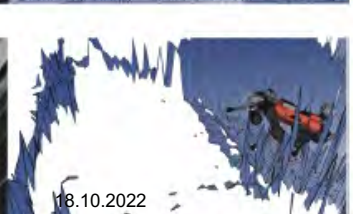
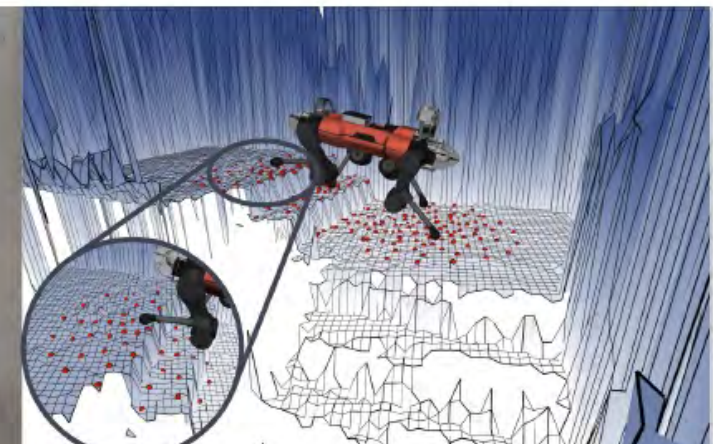
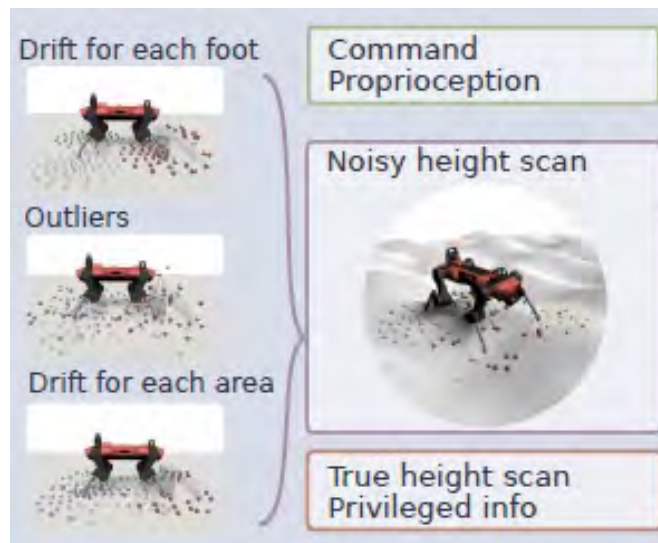


Foot trapping reflex

Proprioceptive memory



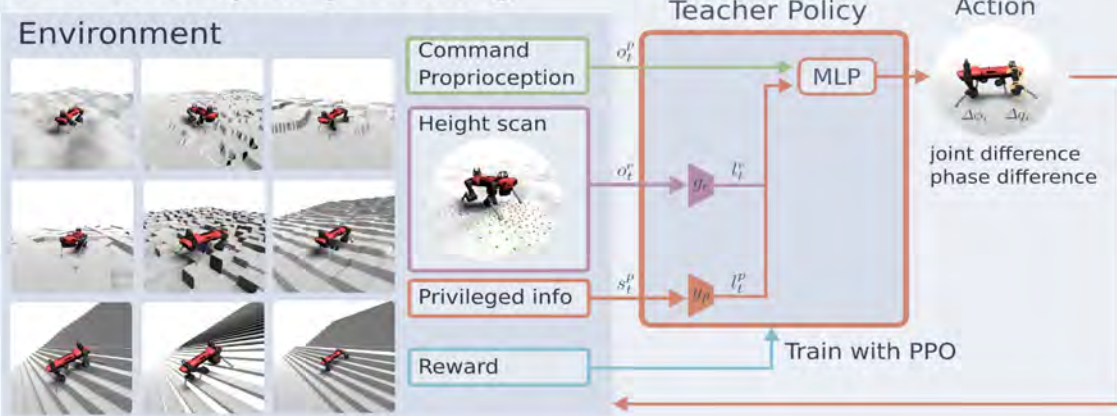
Learning-based locomotion including perception



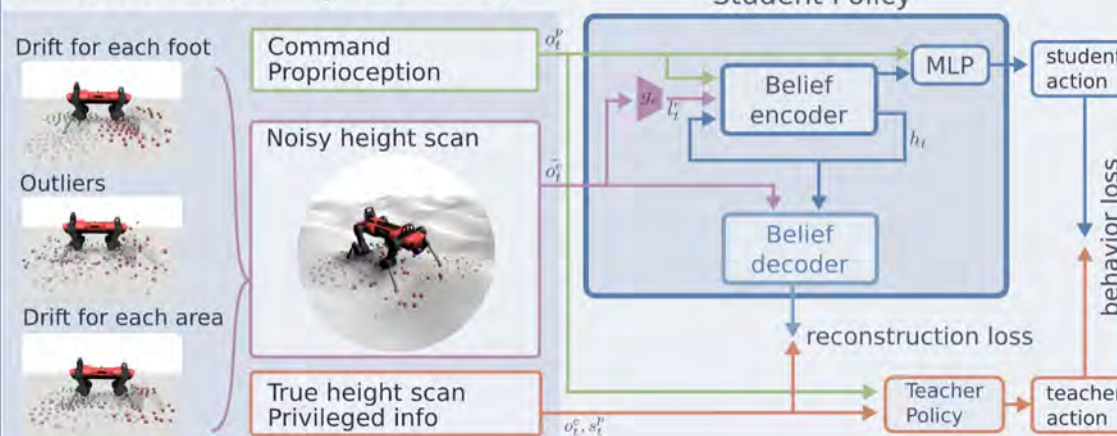
Teacher-Student training

[T. Miki, J. Lee, J. Hwangbo, L. Wellhausen, V. Koltun, and M. Hutter, "Learning robust perceptive locomotion for quadrupedal robots in the wild," *Science Robotics*, 2022.]

1. Teacher policy training

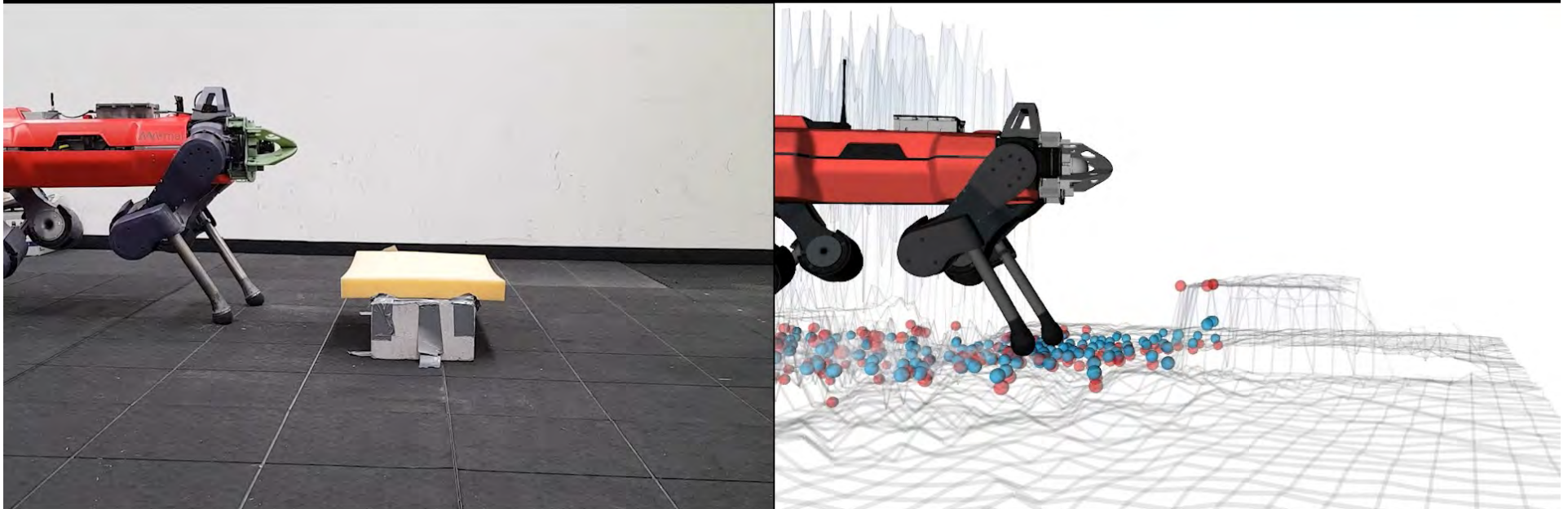


2. Student policy training



What is recognized in the belief state?

Red : Input from map
Blue : Estimated terrain



Soft obstacle



Robustness



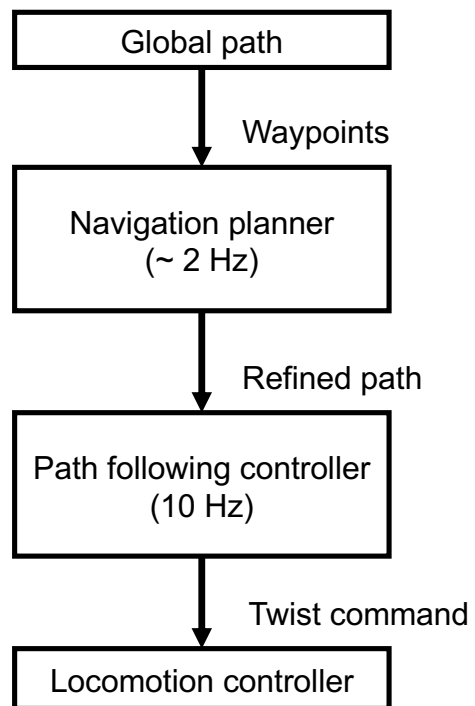


Part 3: Navigation



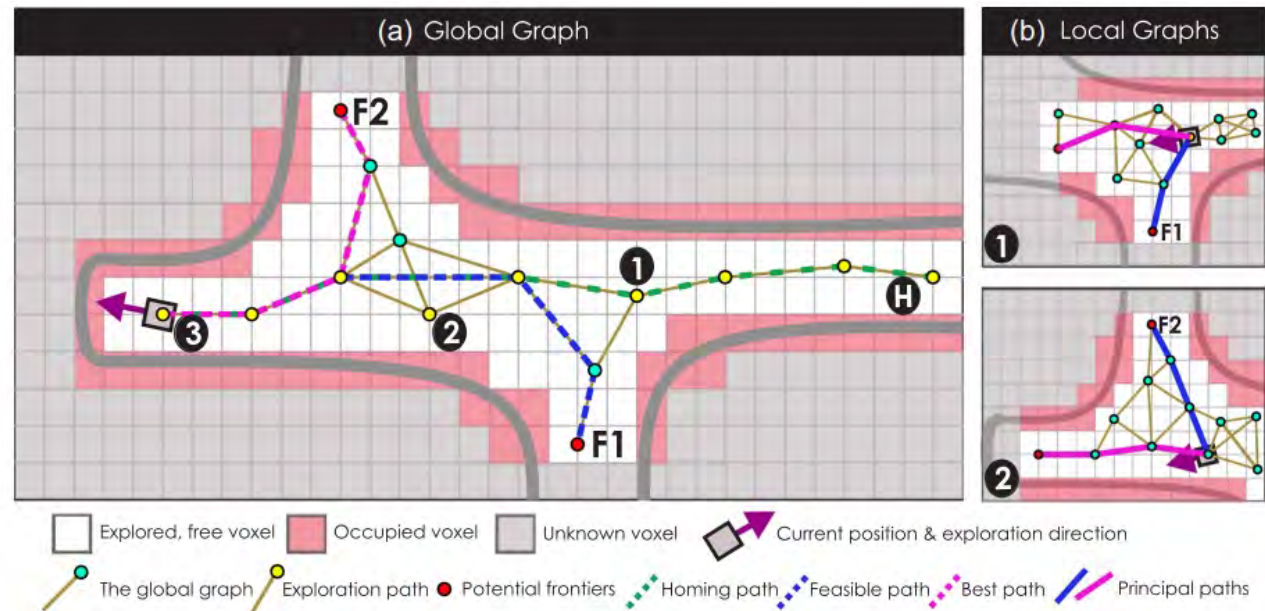
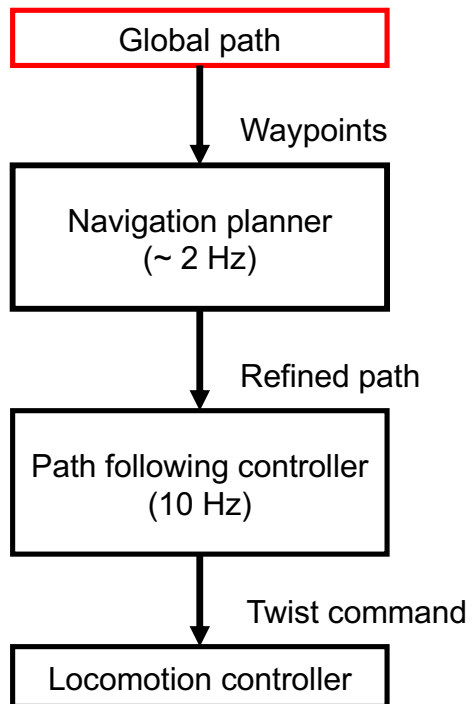
Conventional approach

Planning assumes static environment



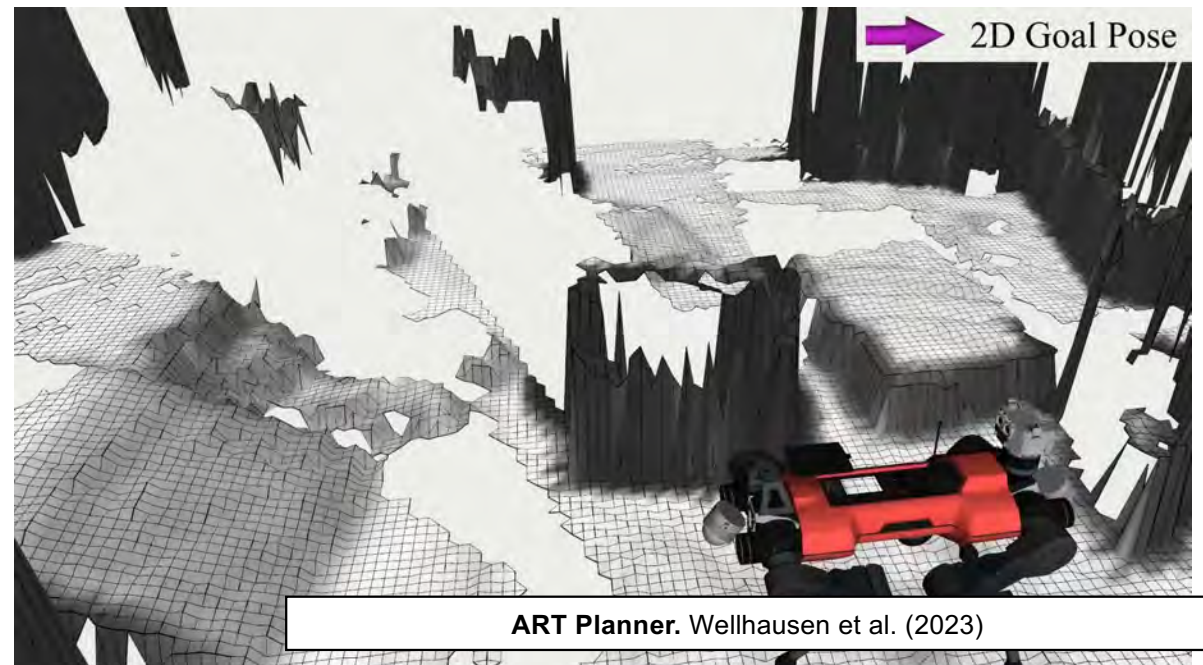
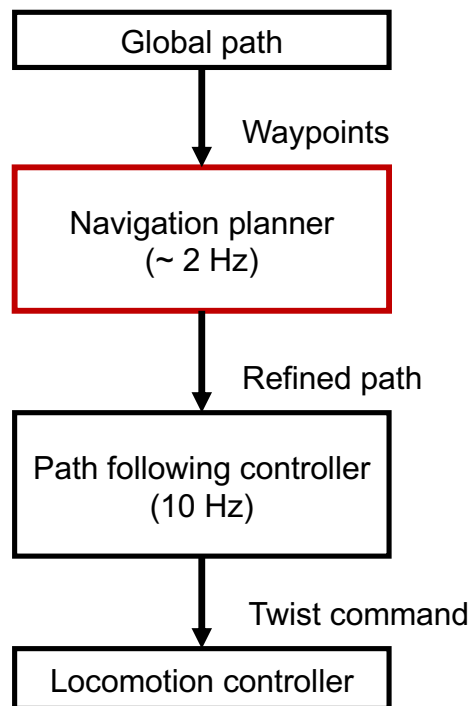
Conventional approach

Planning assumes static environment

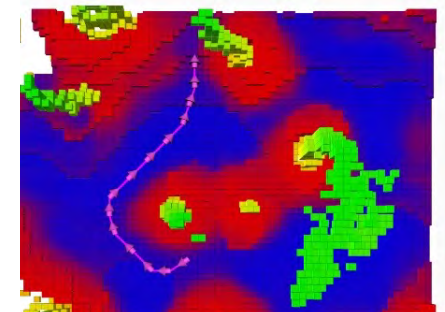
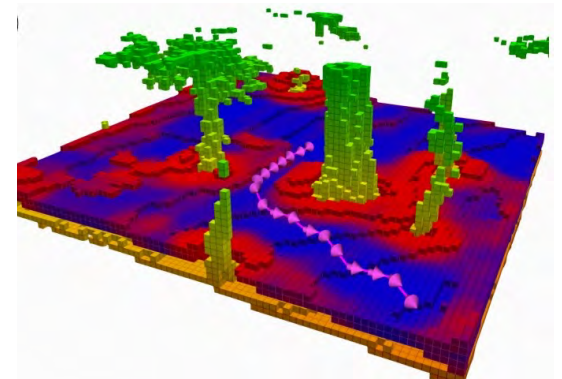
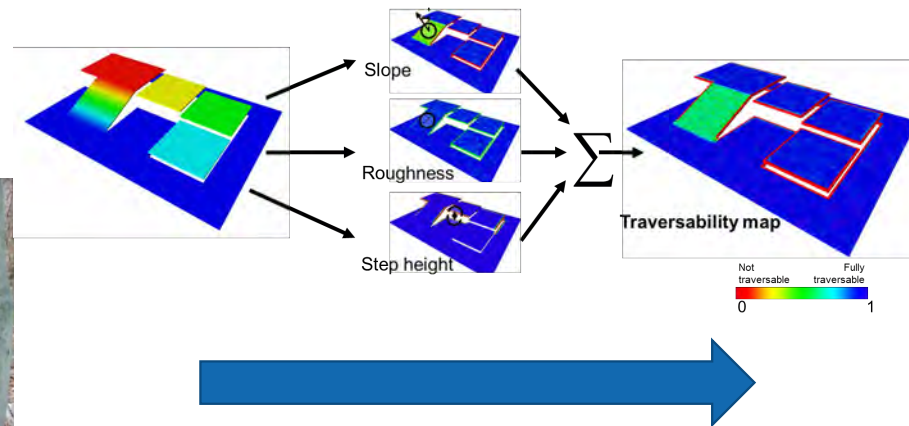


Conventional approach

Planning assumes static environment

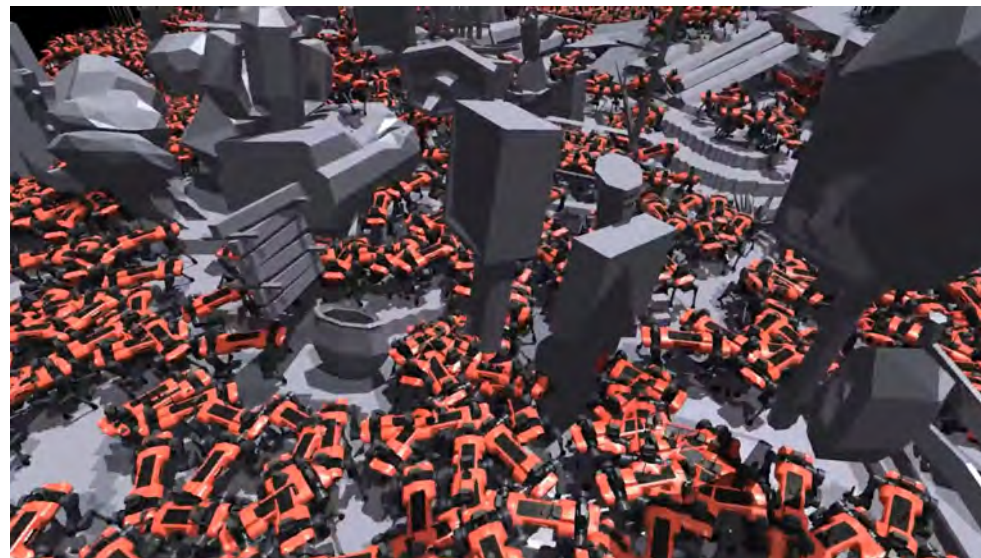
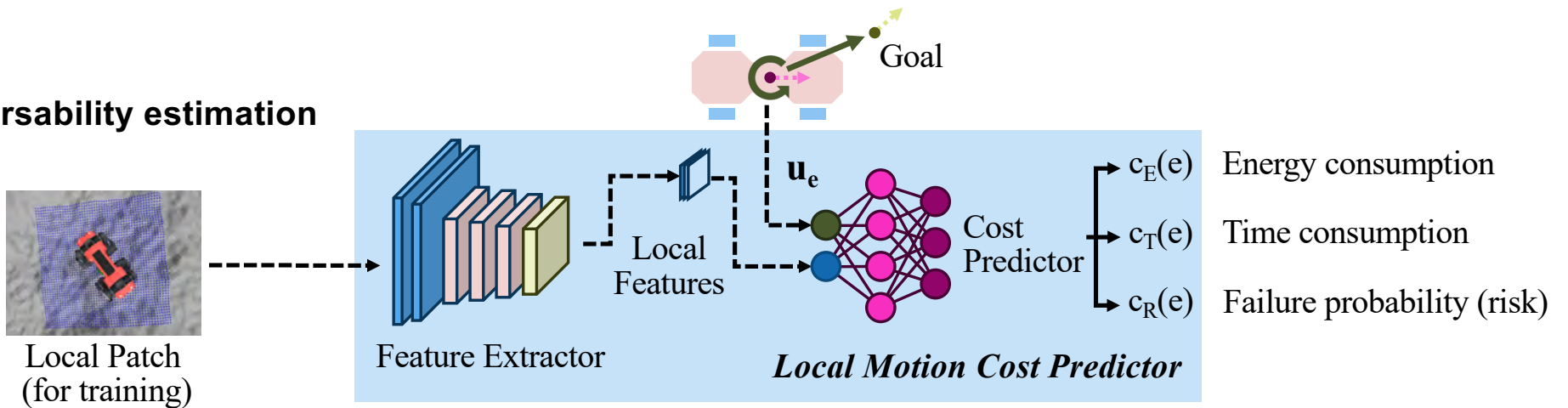


Traversability estimation and navigation



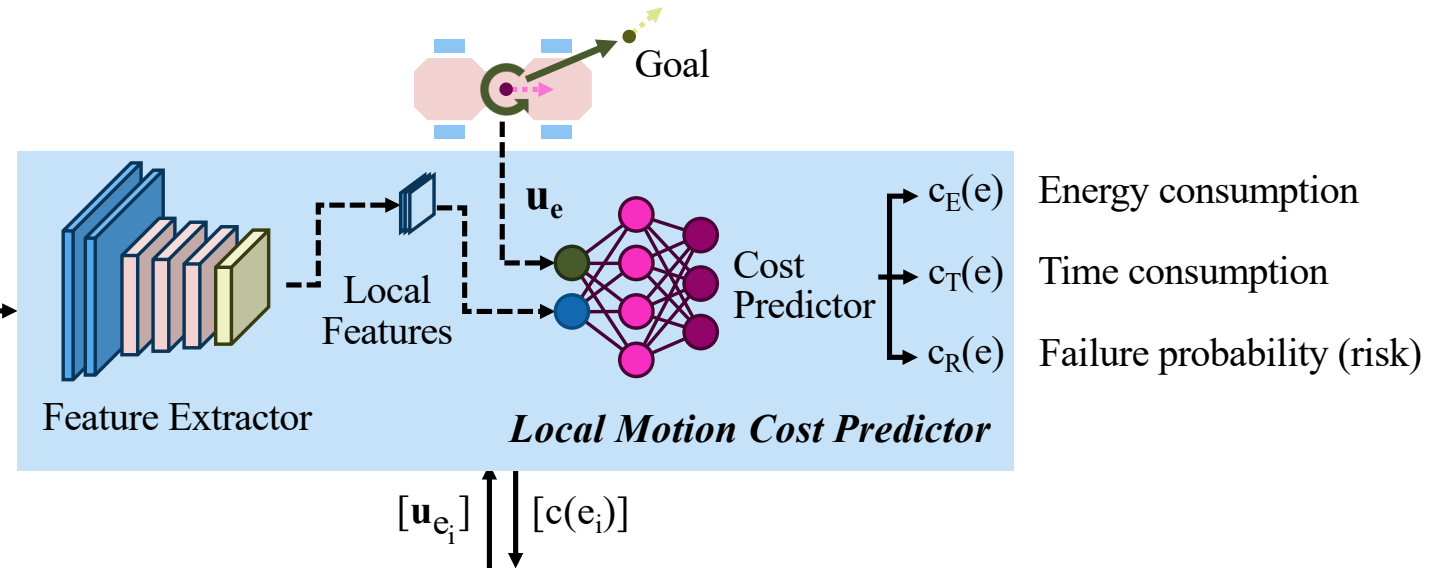
Finding the right local path

- Traversability estimation

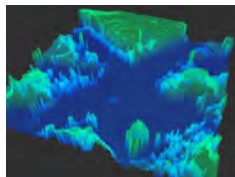


Finding the right local path

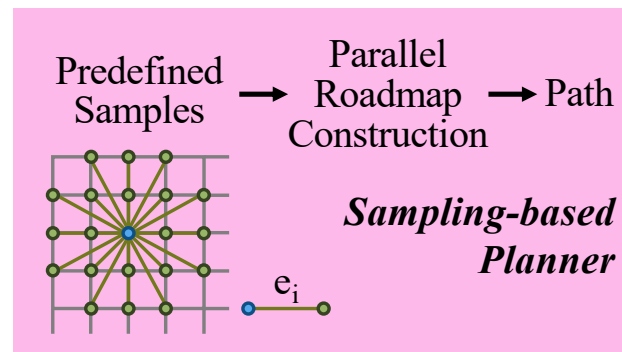
- Traversability estimation



- Find the best path

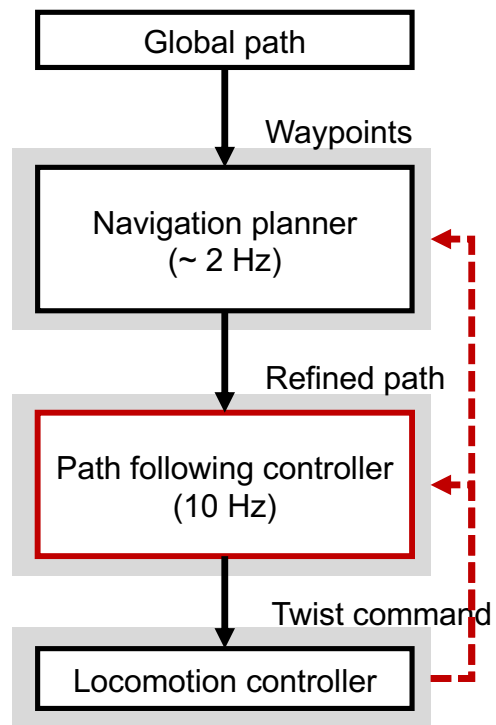


Global Map



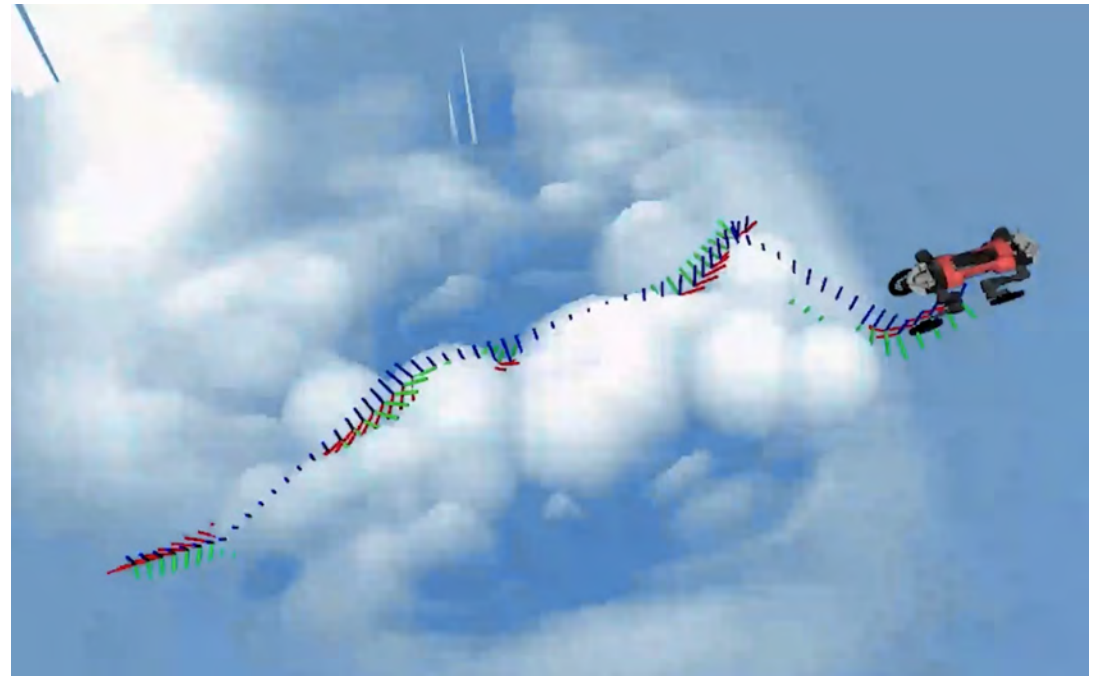
Conventional approach

Dynamics-unaware control and delayed response



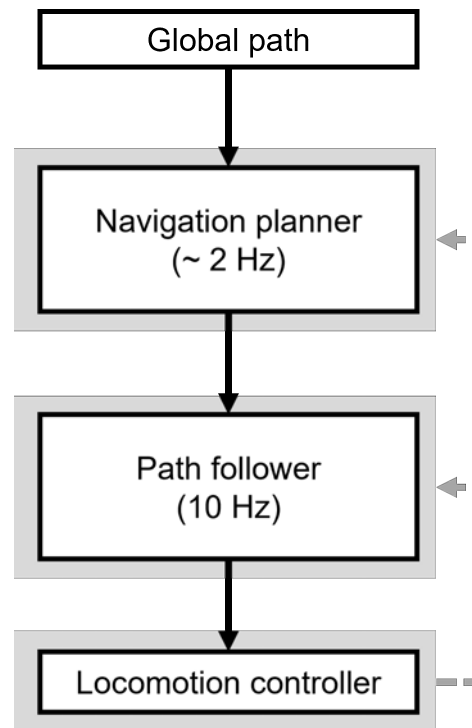
**Information
loss**

- + communication delay
- + computation delay
- + abstraction
- ...



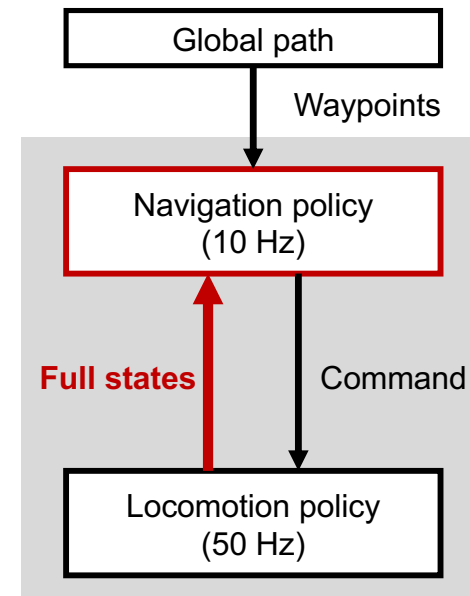
Method (1/4): Revise the system design

Everything into a single module

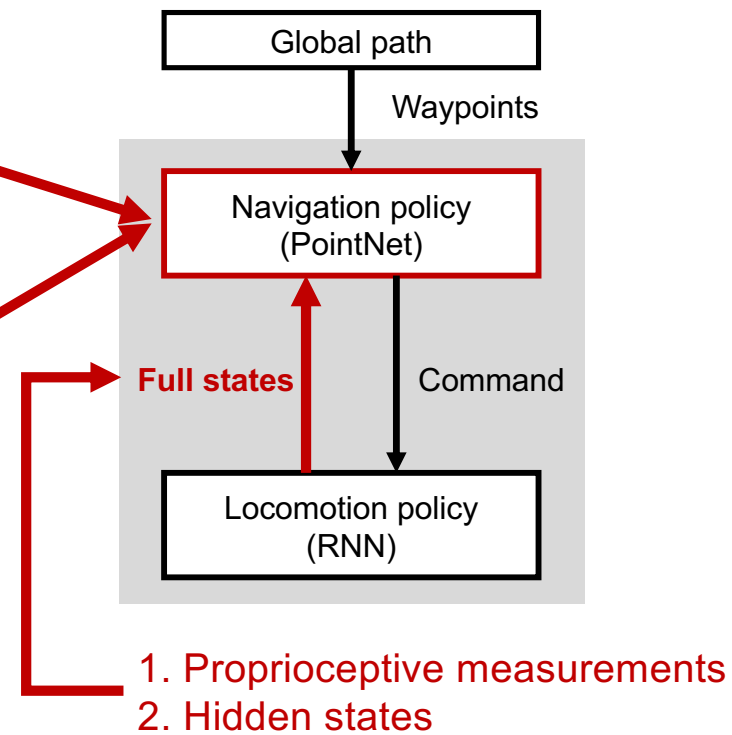
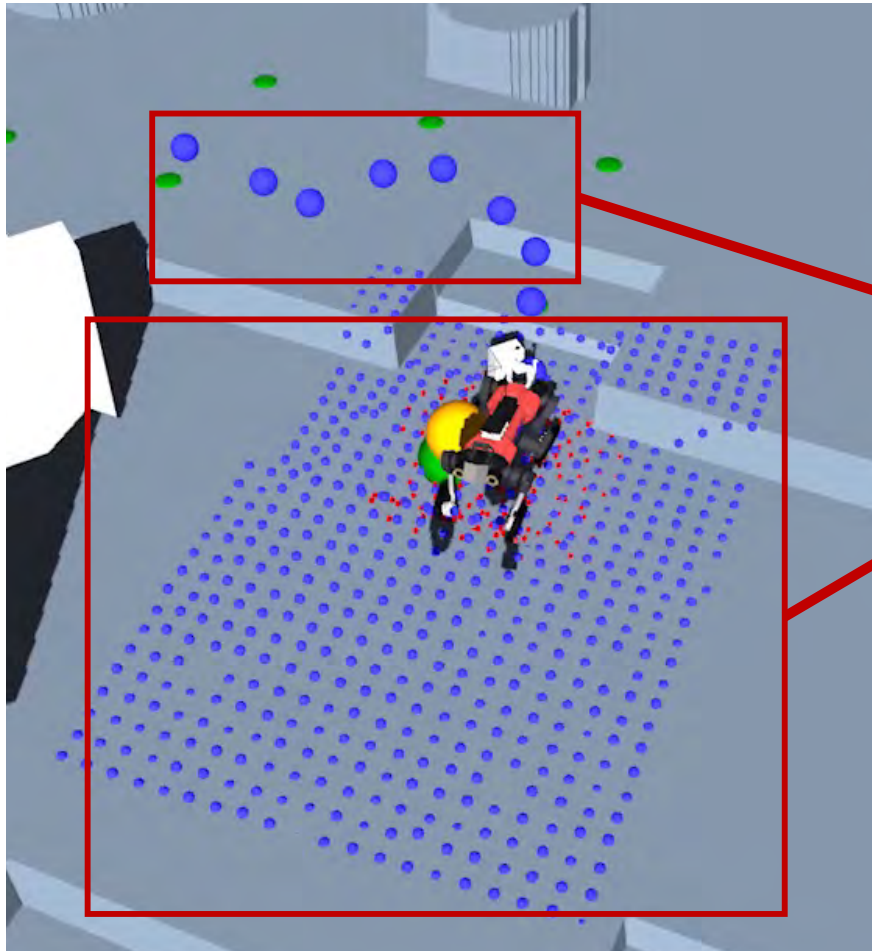


Learning Robust Autonomous Navigation and Locomotion for Wheeled-Legged Robots

Joonho Lee^{1*}, Marko Bjelonic², Alexander Reske², Lorenz Wellhausen²,
Takahiro Miki¹, Marco Hutter¹



Method (2/4): Revise the system design



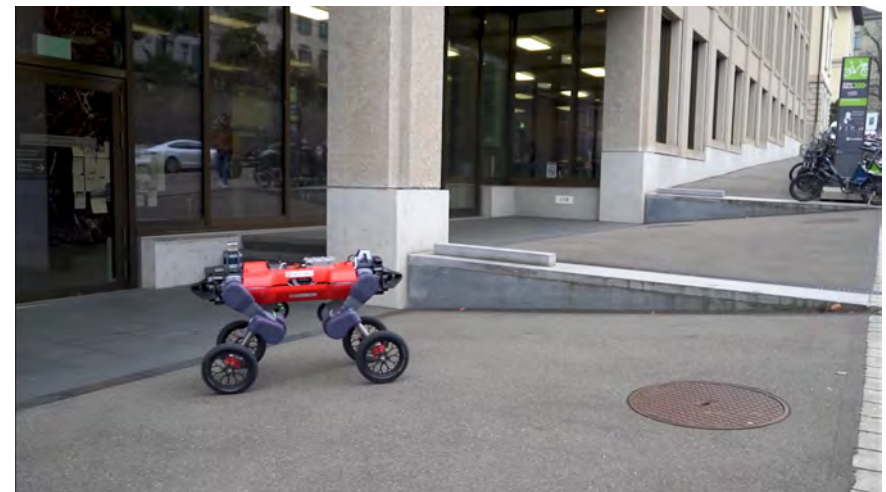
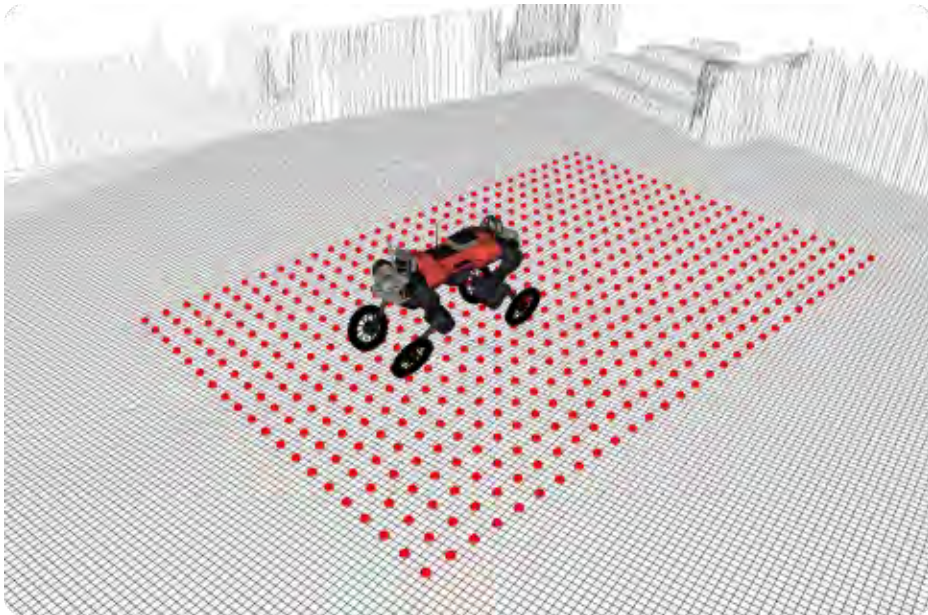
Fast and dynamics-aware control

The resulting navigation controller is very reliable



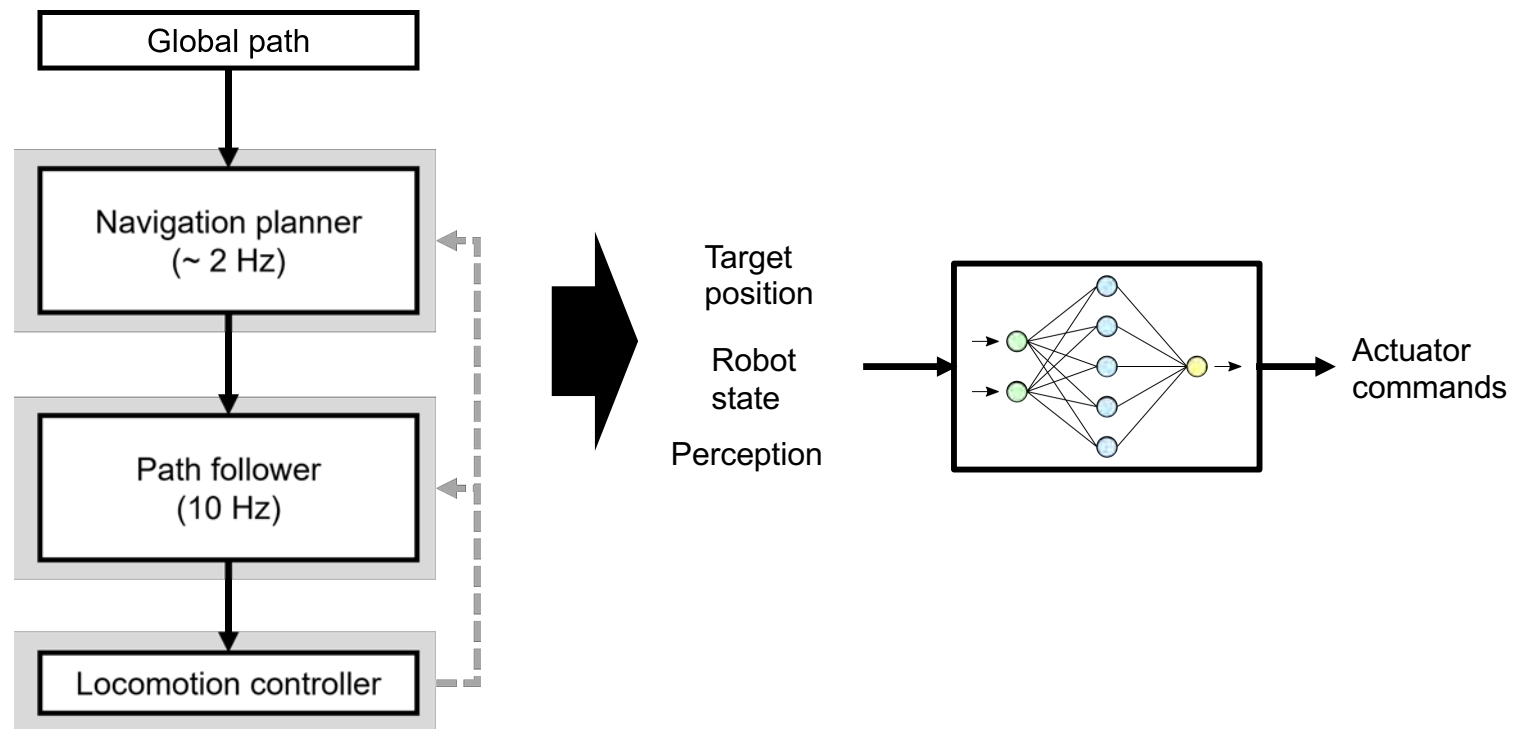
Exploration behavior

Limited field of view → Overcomes with exploration

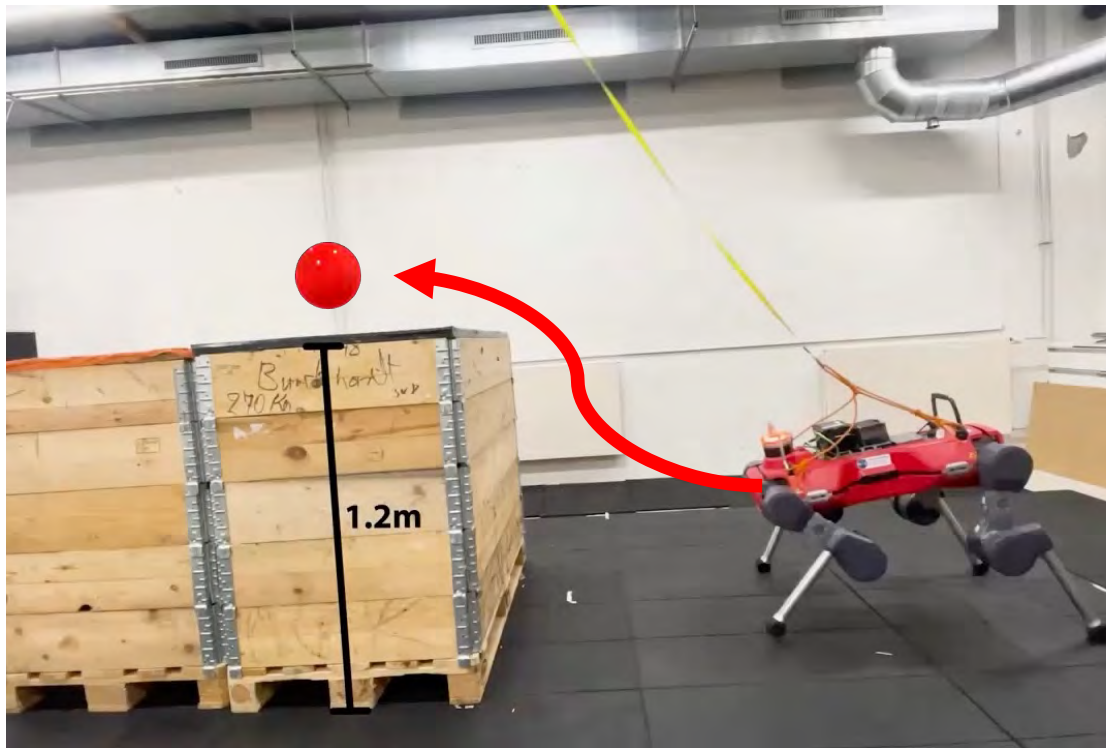


Method (1/4): Revise the system design

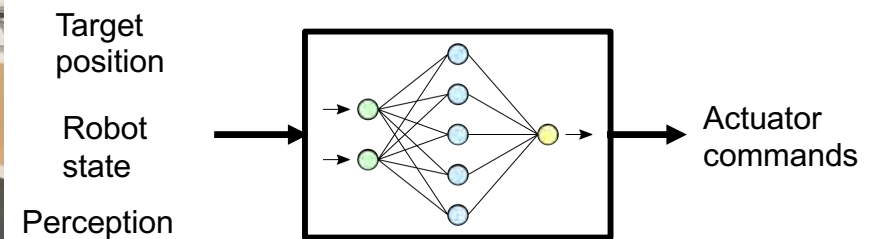
Everything into a single module



Avoid human guidance - Let the robot figure out how to move

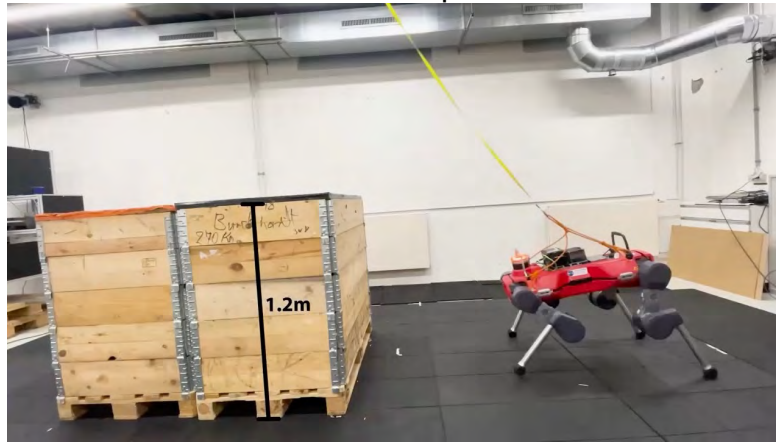


[D. Hoeller, N. Rudin, E. Sako, M. Hutter,
ANYmal parkour: Learning agile navigation for quadrupedal robots.
*Sci. Robot.*9,eadi7566(2024).]



Locomotion Module

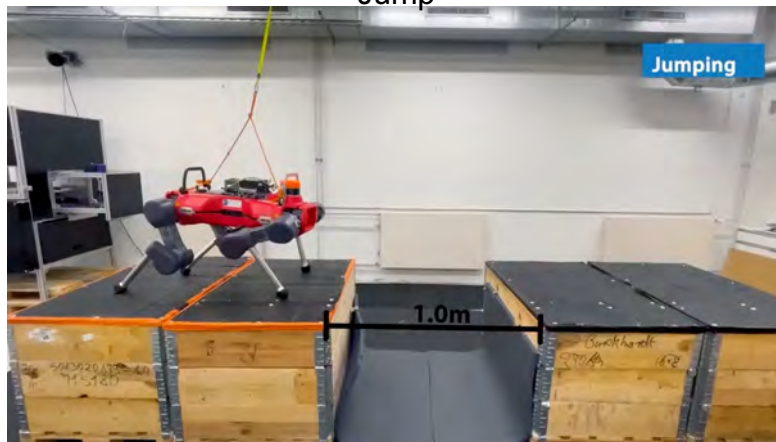
Climb up



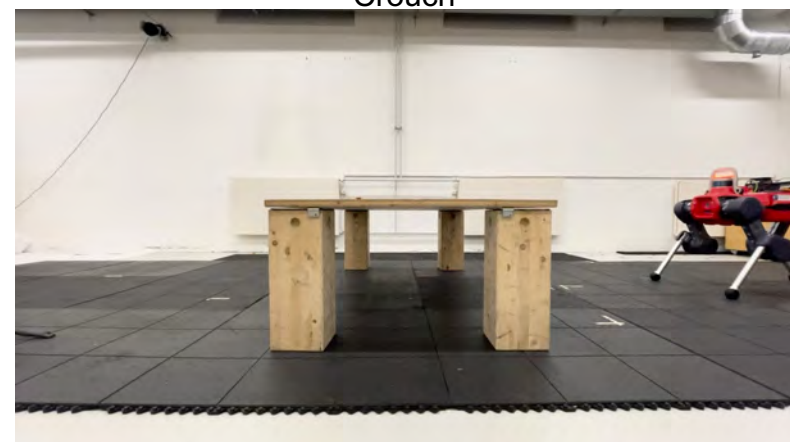
Climb down



Jump

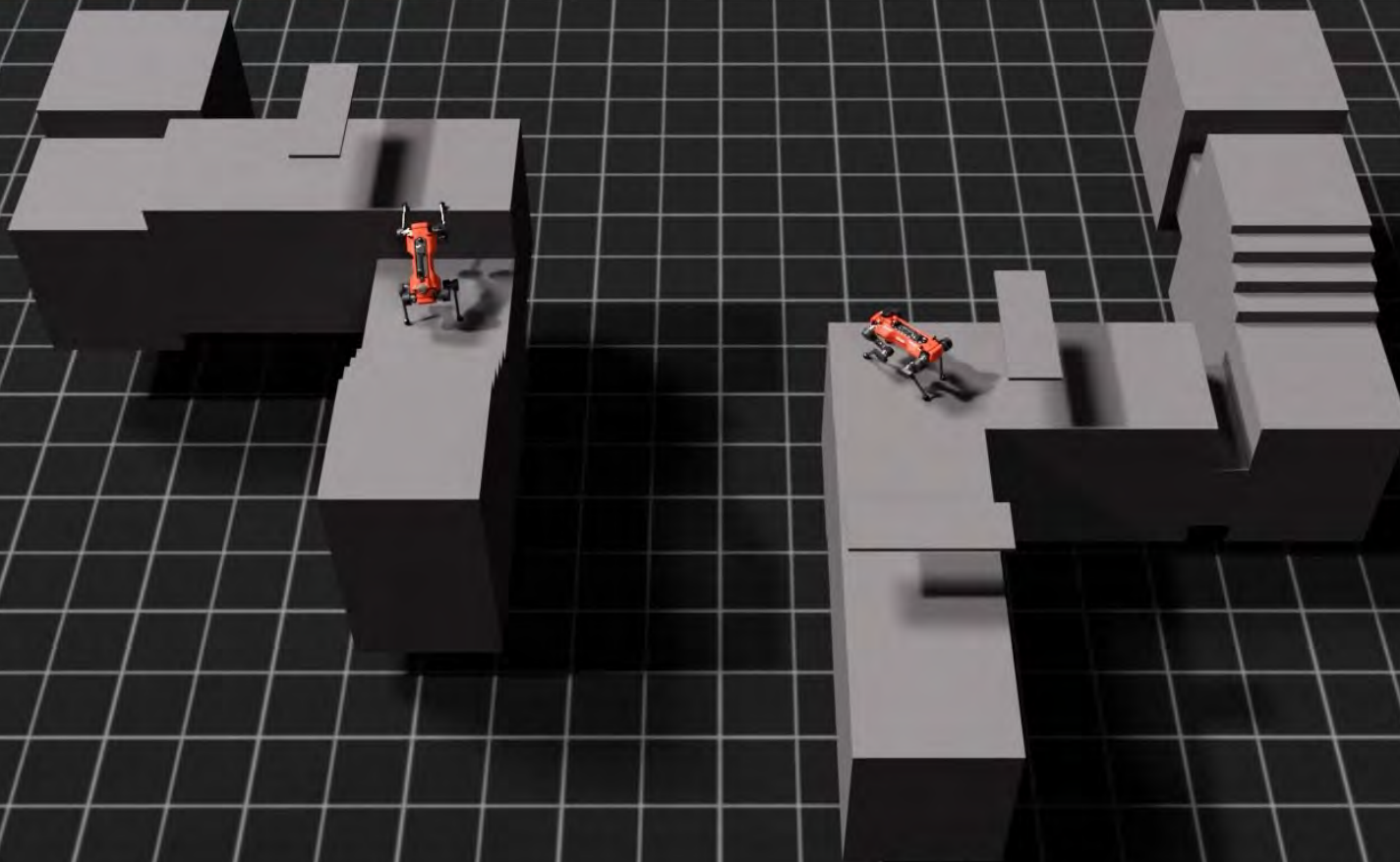


Crouch





Training in Simulation







- Onboard sensing only
- No handcrafting
- No a priori knowledge of the environment





ANYmal perception

Velodyne Lidar



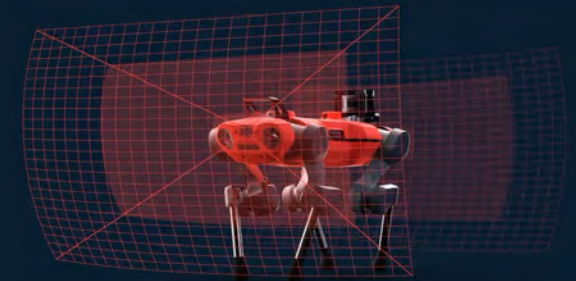
RTK GPS

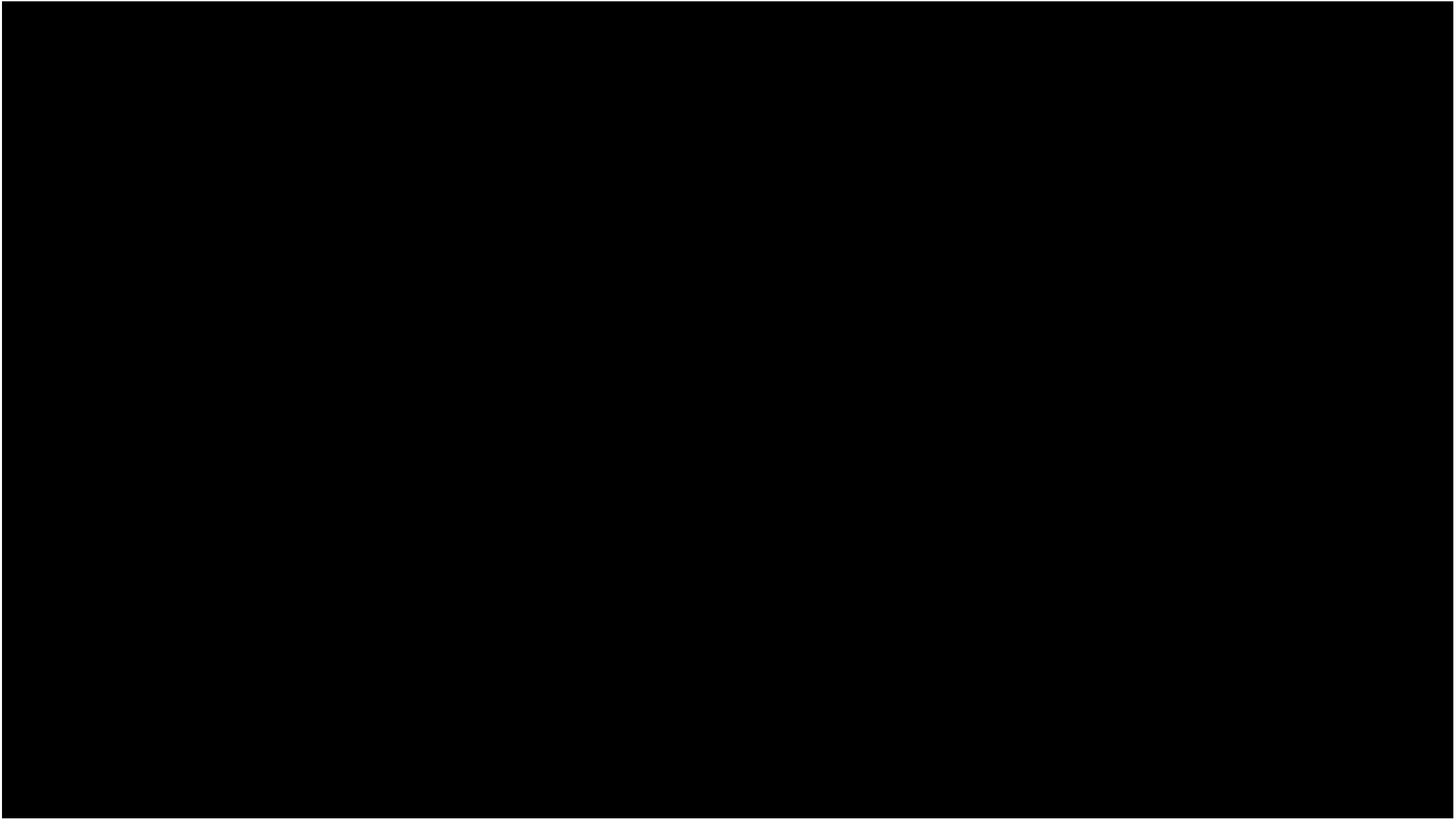


4-6x active stereo



2 x RGB wide angle







Traversability estimation and navigation

- Depends on the Hardware (Robot) and Software (Motion Control)
- Depends on the Terrain (Geometrical Obstacles, Semantics, Slipping)



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Visual Traversability Estimation

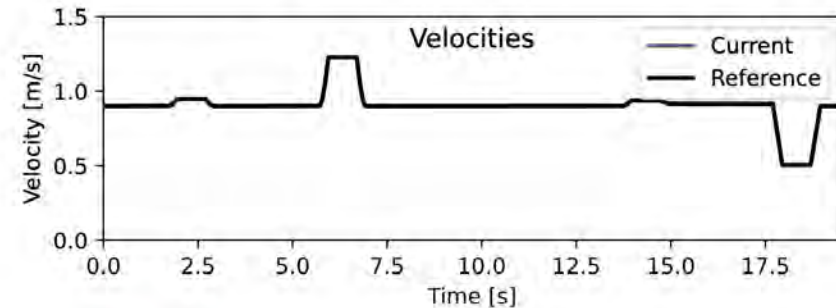


Problem:

- Simulating realistic images and physics is hard
- Real-world data with labels is expensive

Solution:

- Self-supervised learning
- Adaptation during deployment from few data
- Supervision by velocity-tracking error



[Frey, J., Khattak, S., Patel, M., Atha, D., Nubert, J., Padgett, C., Hutter, M., & Spieler, P. (2024). *RoadRunner - Learning Traversability Estimation for Autonomous Off-road Driving*.]

[Mattamala, M., Frey, J., Libera, P., Chebrolu, N., Martius, G., Cadena, C., Hutter, M., & Fallon, M. (2024). *Wild Visual Navigation: Fast Traversability Learning via Pre-Trained Models and Online Self-Supervision*.]

Visual Traversability Estimation



Problem:

- Simulating realistic images and physics is hard
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Solution:

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use high-dimensional features from pre-trained self-supervised models,

- implicitly encode semantic information
- massively simplifies the learning task



Visual Traversability Estimation

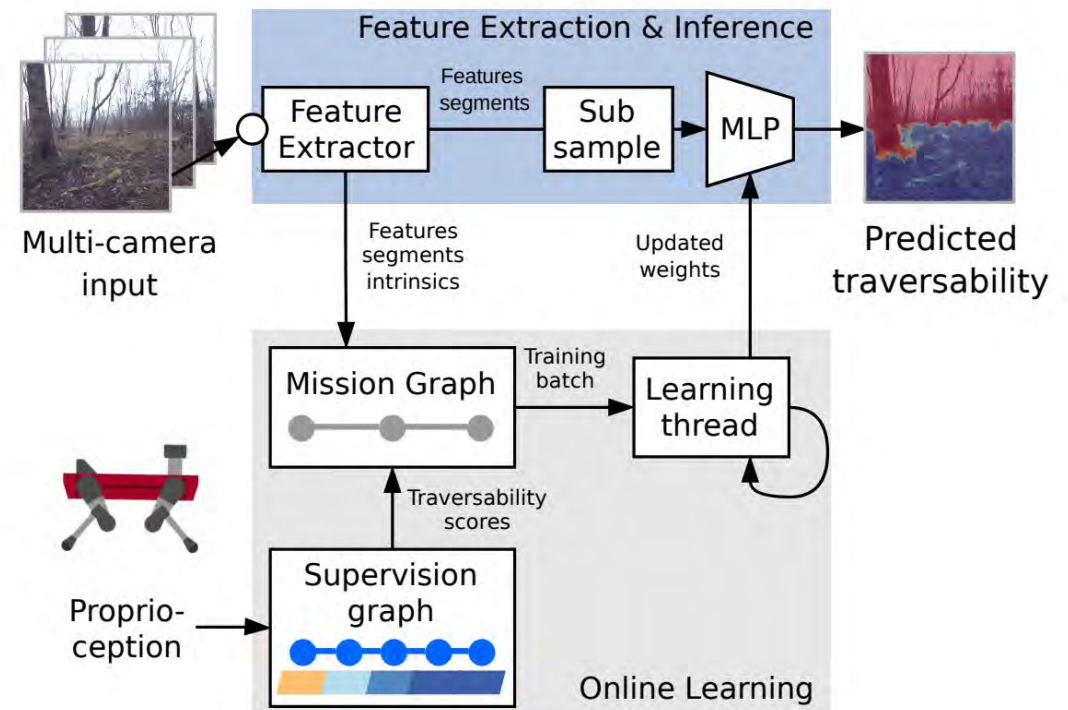


Problem:

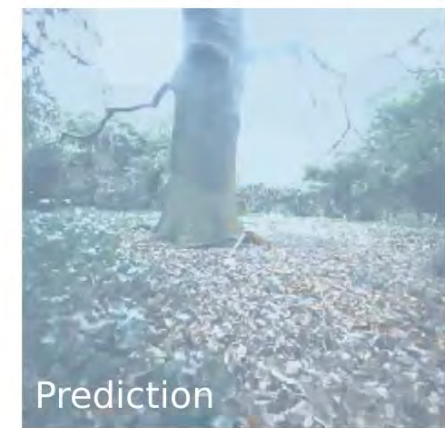
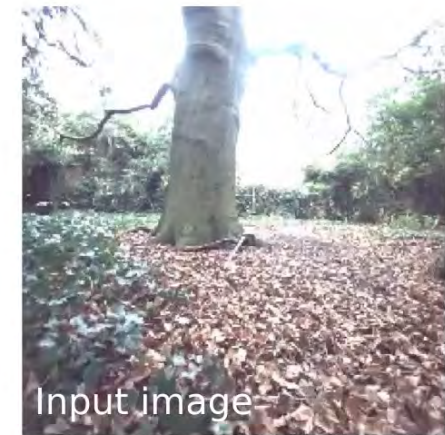
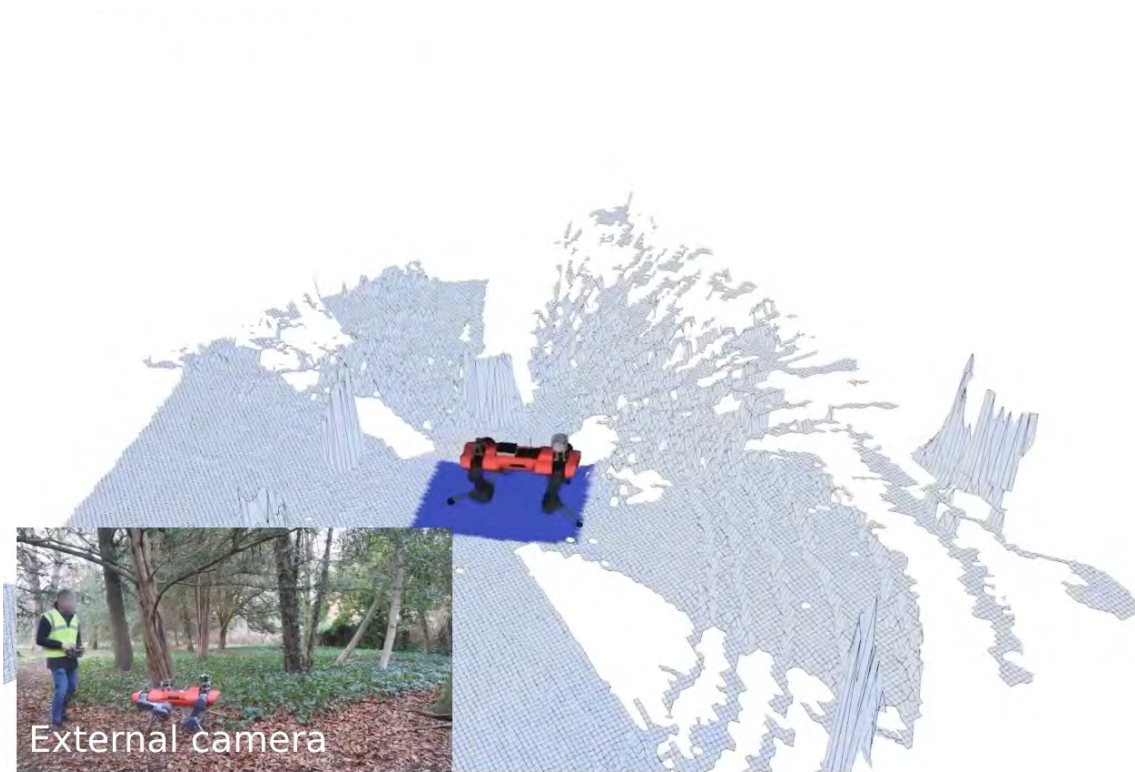
- Simulating realistic images and physics is hard
- Real-world data with labels is expensive

Solution:

- Self-supervised learning
- Adaptation during deployment from few data
- Supervision by velocity-tracking error
- Online training



Visual Traversability Estimation V1





Part 4: Applications

DARPA SubT Challenge (2019-2021)

Mobile robots for challenging environments

Goal: map, navigate, search, and explore complex underground environments



TUNNEL SYSTEMS

Tunnels can extend many kilometers in length with constrained passages, vertical shafts, and multiple levels.



URBAN UNDERGROUND

Urban underground environments can have complex layouts with multiple stories and span several city blocks.



CAVE NETWORKS

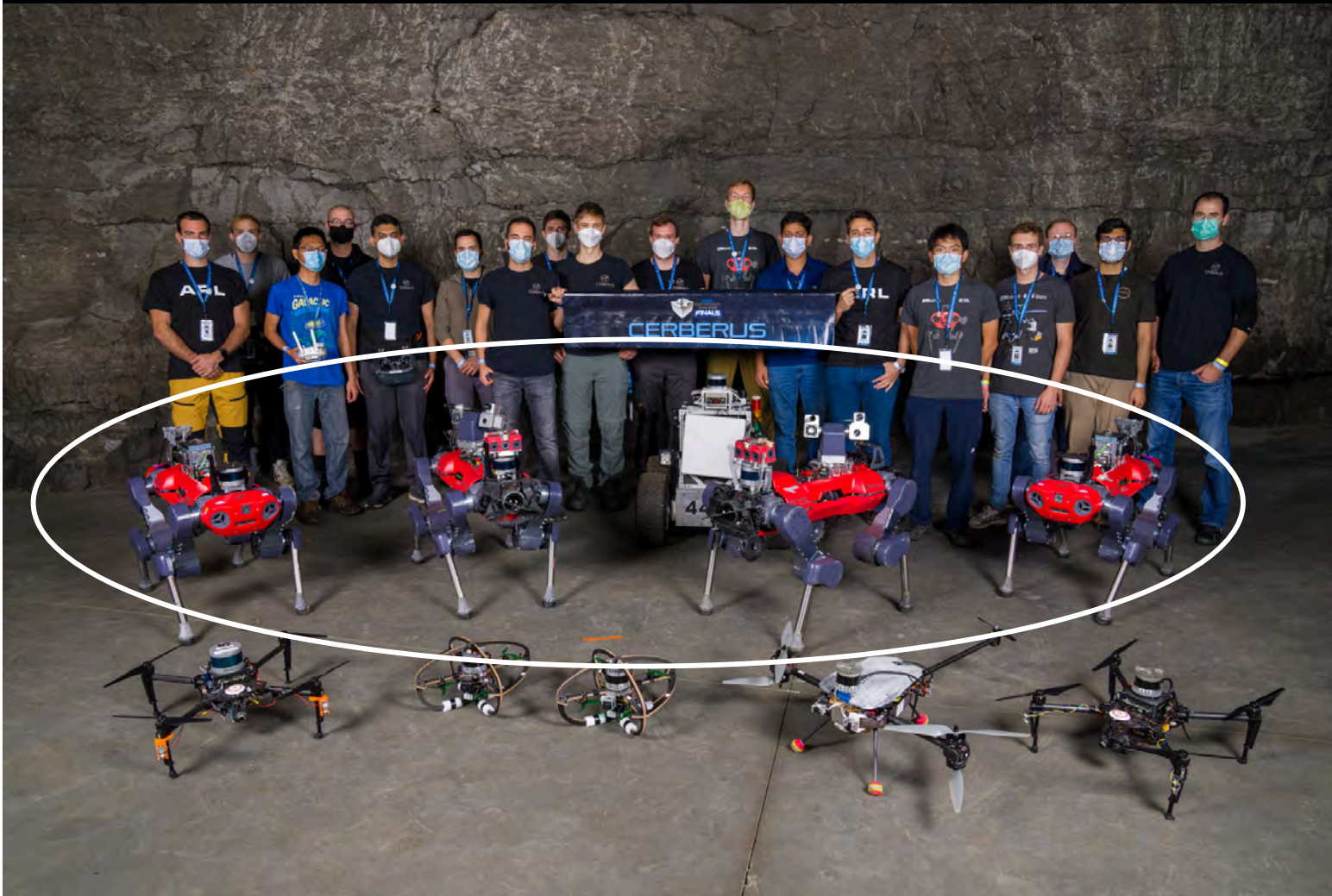
Natural cave networks often have irregular geological structures, with both constrained passages and large caverns.

Challenges:

- unstructured & unknown environment of different scale,
- rough and hardly traversable terrain,
- degraded perception,
- missing communication, ...



DARPA SubT Challenge – Mobile robots for challenging environments



Team CERBERUS

At Finals:

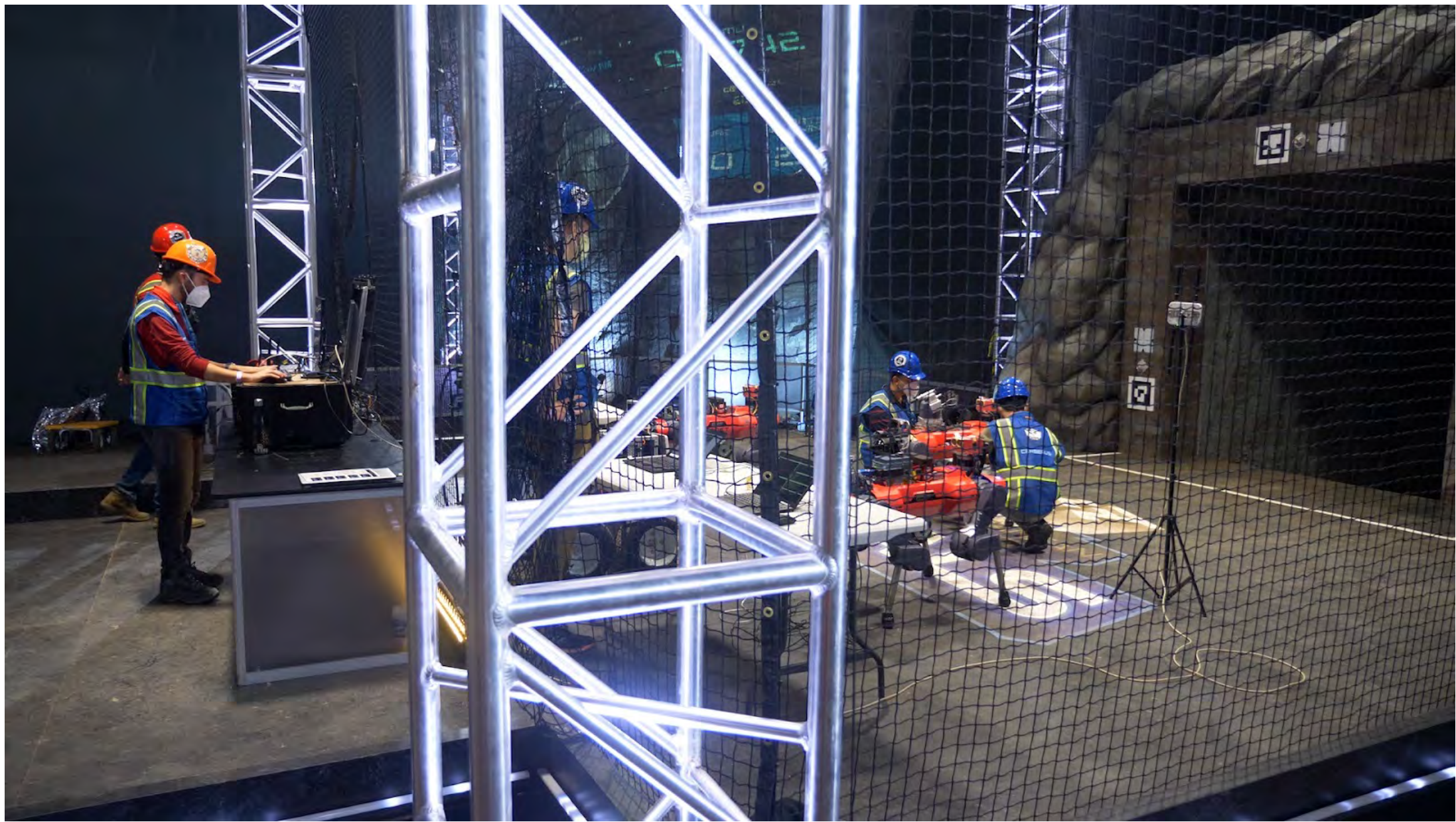
ARL – UNR/NTNU

RSL – ETHZ

ASL – ETHZ

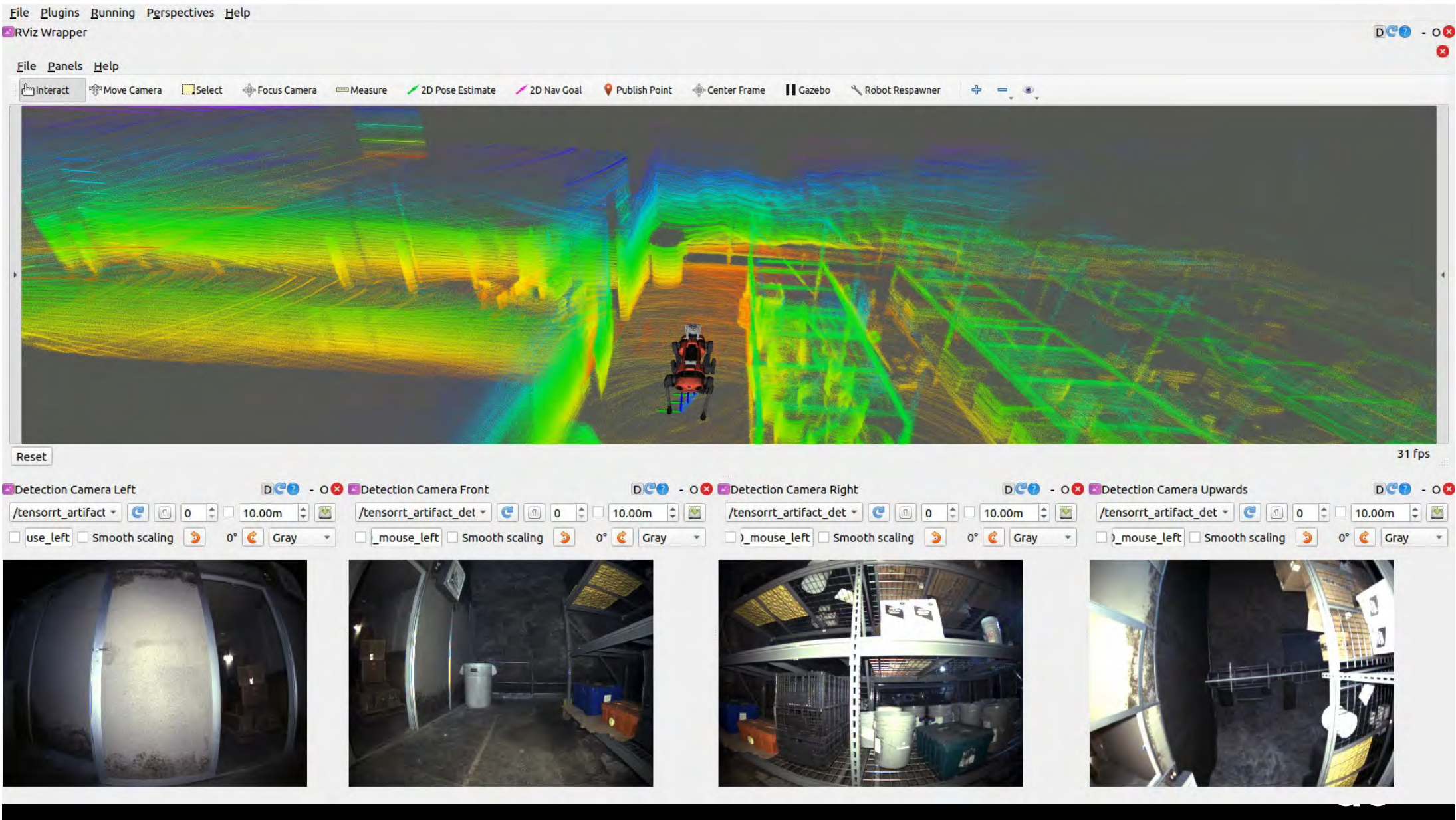
Other Contributors:

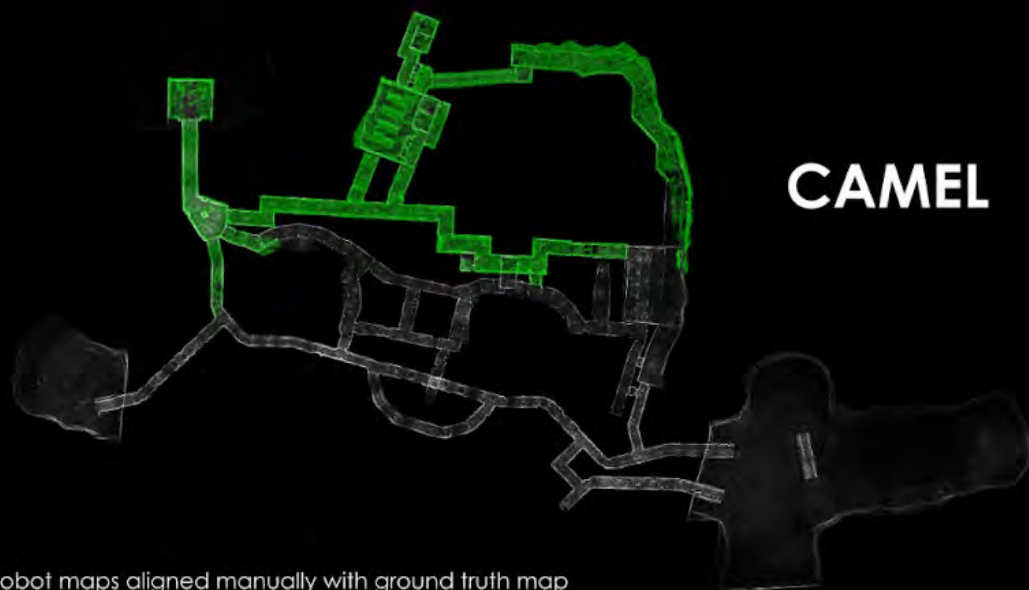
Oxford, Flyability, Berkeley, SNC





18.10.2022





* Robot maps aligned manually with ground truth map



CERBERUS

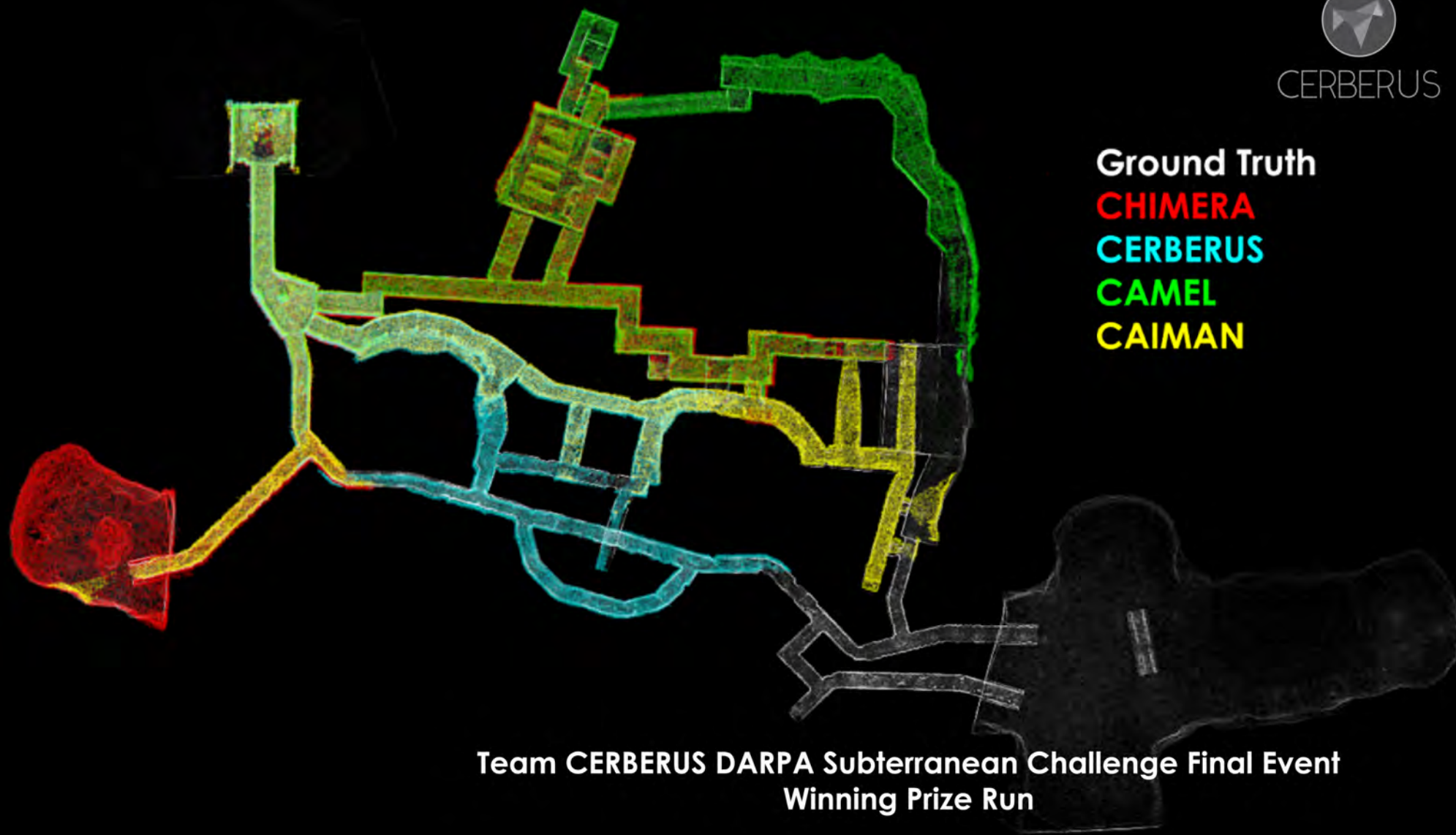
Ground Truth

CHIMERA

CERBERUS

CAMEL

CAIMAN



Team CERBERUS DARPA Subterranean Challenge Final Event
Winning Prize Run

We are on the verge of the next robotic revolution

AUTONOMOUS INDUSTRY




Enabled by autonomous mobile robots




SMART WAREHOUSING





Enabled by 600'000 warehouse robots in operation

AUTOMATED MANUFACTURING

Enabled by 3 million industrial robots in operation

-  Workforce shortage
-  Repetitive motions
-  Structured tasks

-  Workforce shortage
-  Repetitive tasks
-  Structured environment

-  Workforce shortage
-  Repetitive work
-  Structured problem
-  Dangerous environment





AMbotics

Industrial plant inspection



- ✓ Periodic condition monitoring and hazard detection of equipment
- ✓ Remote sensing from control room

Thank you!

More information:

- leggedrobotics.com
- youtube.com/leggedrobotics
- bitbucket.org/leggedrobotics
- github.com/leggedrobotics

Start to collaborate

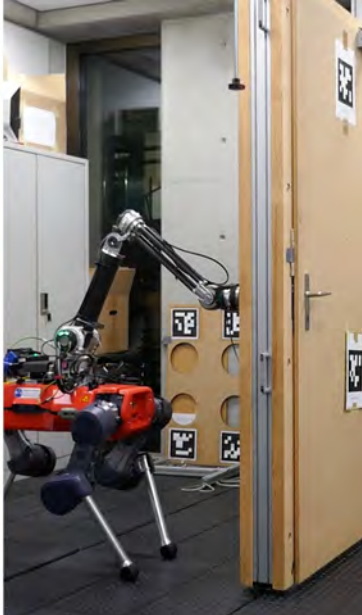
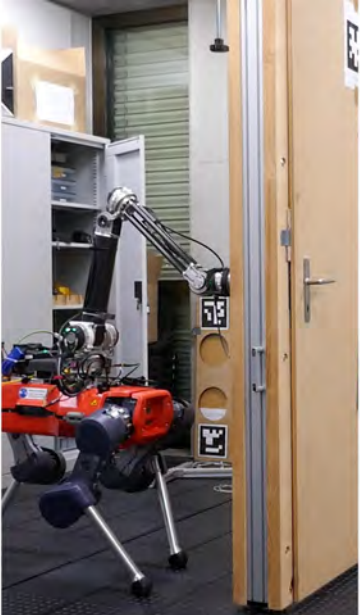
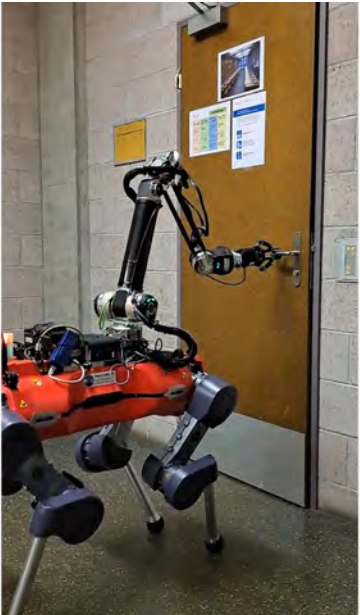
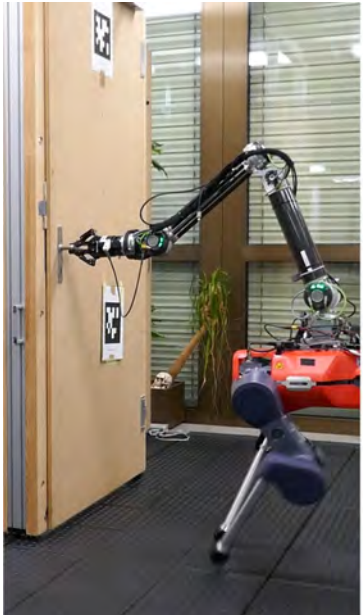
- anymal-research.org



Possible exam questions

- Sketch a typical framework required to enable a legged robot to autonomously navigate unknown environments. List the most important building blocks.
- What type of sensors are often used on legged robots and what are they used for?
- Provide different abstraction levels for legged robots. What is this useful for?
- Motion planning for legged systems is a hybrid problem. What is a hybrid problem? What are possible approaches to solve it?
- What is the reality gap and how could one overcome it?
- Reinforcement learning allows training a locomotion policy for legged robots. What are typical observations (i.e. input signals to the neural network) and actions (i.e. output signals of the neural network) for a robot that walks blindly (i.e. without lidar or camera sensors)?
- How can a robot identify, if a terrain is traversable?
- What are possible fields of application of legged robots?

Part 5: Future stuff











Important Events

- 1.11.2024 Swiss Robotics Day (www.swissroboticsday.ch)
- 6.12.2024 RSL open lab evening (Friday evening, robots & party) www.rsl.ethz.ch