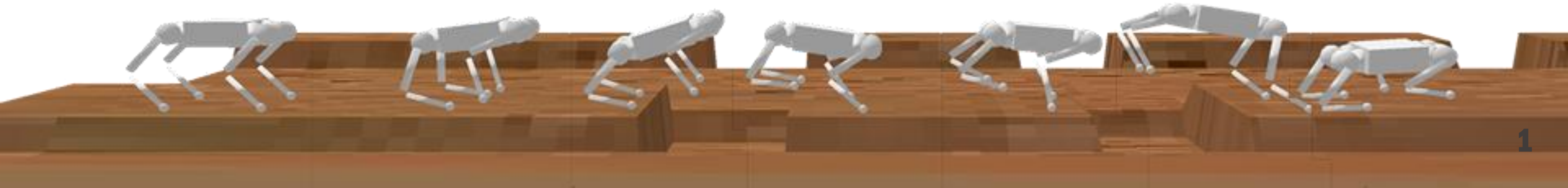
Learn to Jump from Pixels

Margolis, Gabriel B., et al. "Learning to jump from pixels." arXiv preprint arXiv:2110.15344 (2021).

Group 19

Jiajun Hu
Romain Bernadat
Heyun Luan



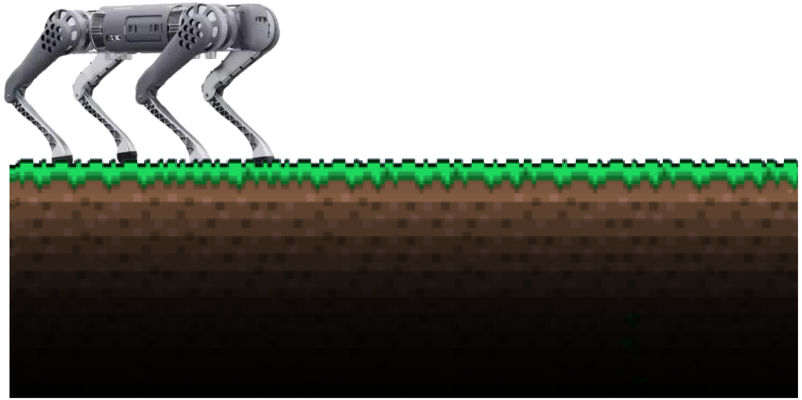
Introduction

Challenge:

- Robots need visual guidance to perform agile motions (e.g., jumping) on discontinuous terrains (e.g., gaps)

This Paper (Depth-based Impulse Control (DIC))

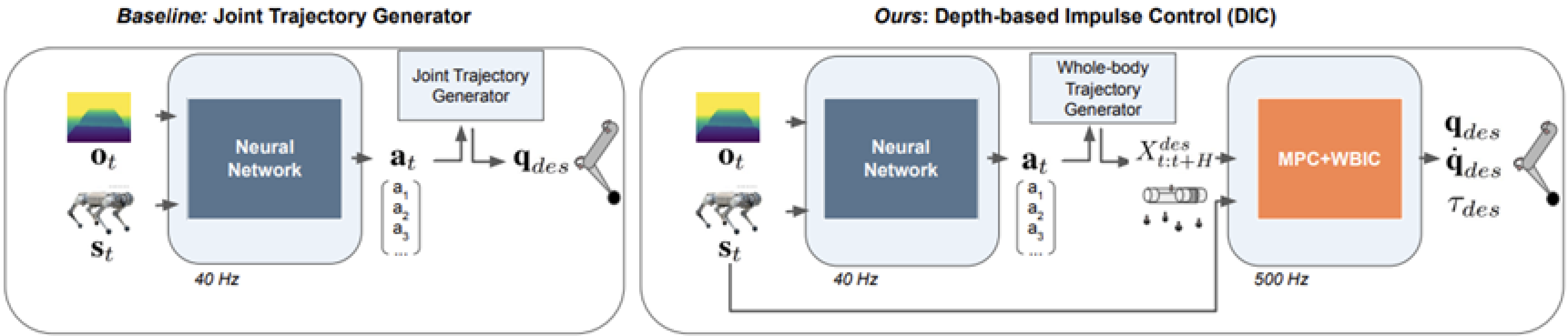
- Robot type: Quadruped
- Sensors: Depth camera + IMU
- Method: Vision-based hierarchical control
  - High level (RL) + Low level (MPC + WBIC)
- Gaits: Unconstraint gaits



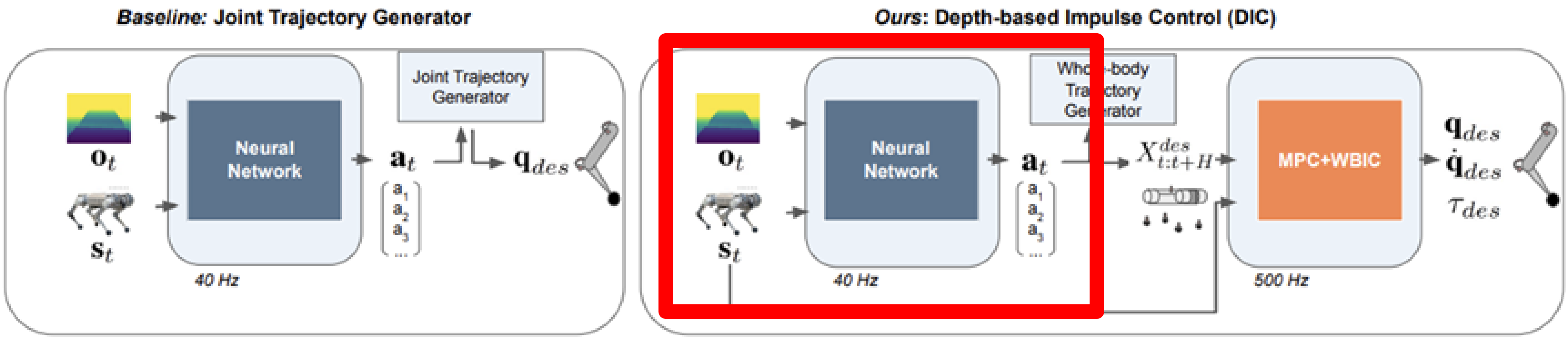
EPFL

Method

Depth-based Impulse Control (DIC) Architecture



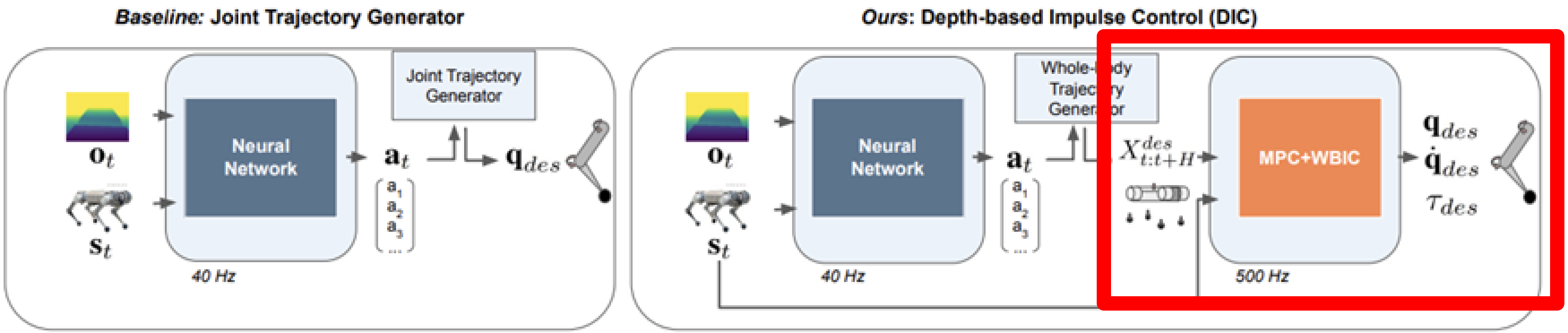
- DIC combines **model-based** and **learning-based** control approaches
- **Generate agile movements using depth data** captured by an onboard depth camera



- A **high-level controller** that processes visual input to determine the desired trajectory of the robot's body and **convert them into actions**:

  - **Body Velocity**: Specifies both the forward and vertical speed, which influences the jump's height and span
  - **Gait Schedule**: Controls the timing of foot contacts with the ground. By adjusting the gait, the high-level controller can change the foot positioning dynamically to suit different obstacles

EPFL

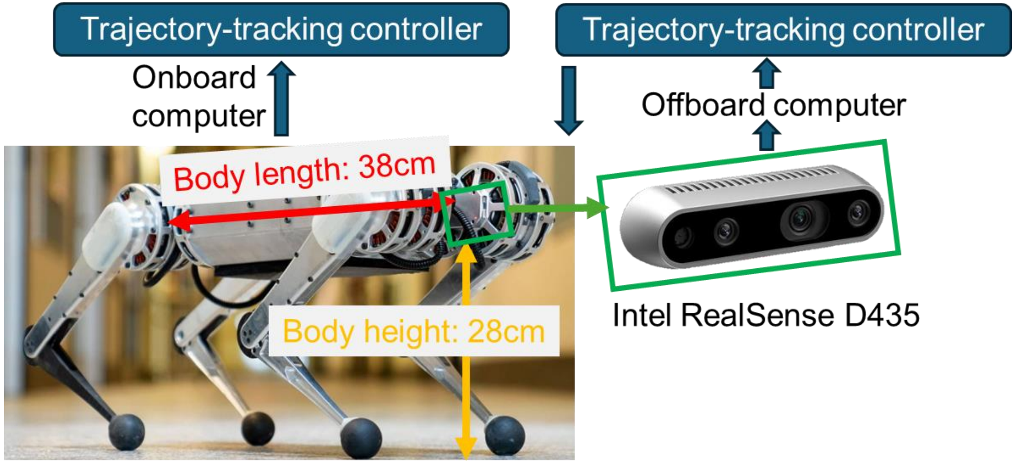


- A **low-level controller** that employs **Whole-Body Impulse Control (WBIC)** to convert high-level commands into ground reaction forces.

WBIC calculates the forces each foot should apply to achieve the trajectory

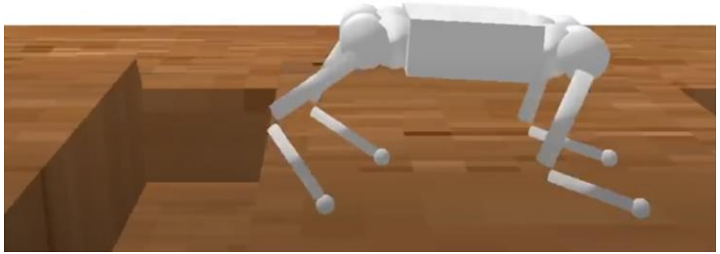
- **Model Predictive Control (MPC)**: Computes desired forces at each foot to follow the planned body trajectory
- **Differential Inverse Kinematics**: Uses the computed forces to generate target joint angles and velocities for each leg

Experiment Setup



MIT Mini Cheetah

Hardware Platform



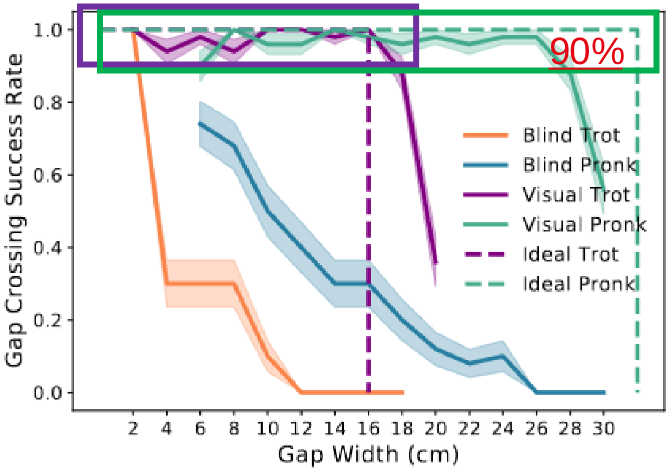
Simulation Platform

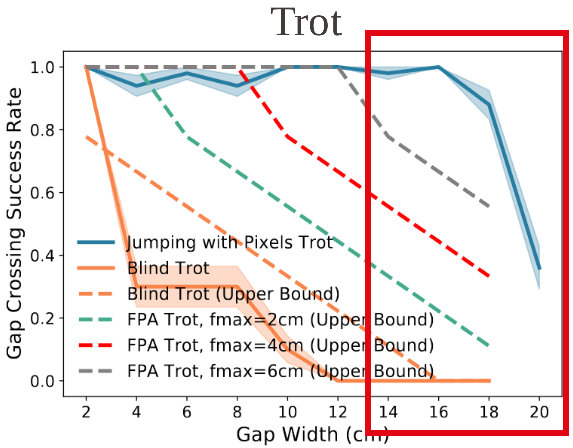
- Training Set:
  - Gap: uniform random width, $W_{min} = 4\text{cm}$, $W_{max} \in [10,20,30]\text{cm}$
  - Flat segments: random width 0.5 to 2.0m
- Test dataset contains novel terrains drawn from the same distribution

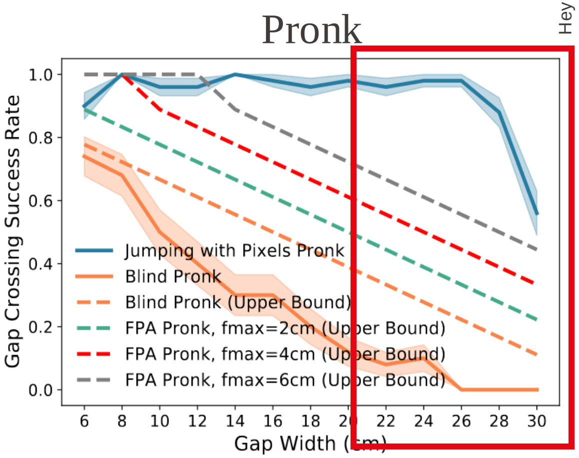
Results: Fixed Gait in Simulation

$$c_{trot} = \begin{cases} [1,0,0,1] & t < \frac{d}{2} \bmod d \\ [0,1,1,0] & t \geq \frac{d}{2} \bmod d \end{cases} \qquad c_{pronk} = \begin{cases} [1,1,1,1] & t < \frac{d}{2} \bmod d \\ [0,0,0,0] & t \geq \frac{d}{2} \bmod d \end{cases}$$

Heyun Luan







- DIC succeeds at above **90%** of gap-crossing attempts for both trotting and pronking.
- DIC outperforms blind locomotion and local foot adaptation (FPA), especially **on large gaps**.

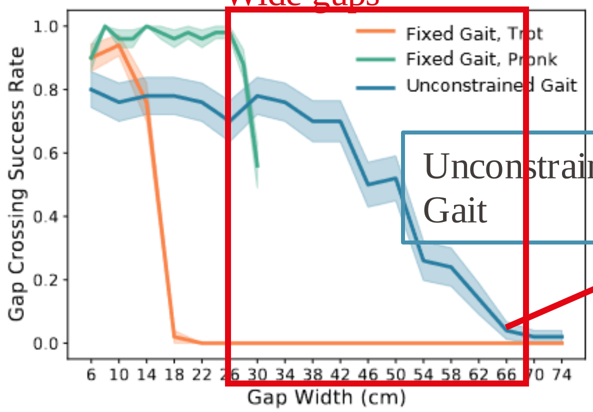
➢ Comparison:

- Blind motion: follows probabilities of gap parameters
- Ideal performance: theoretical limits
- Foot position adaptation (FPA) by local foothold adaptation baseline: model-based baseline, adapt foothold with safety heuristic.

https://sites.google.com/view/jumpingfrompixels/

Results: Unconstrainted Gait in Simulation

Wide gaps

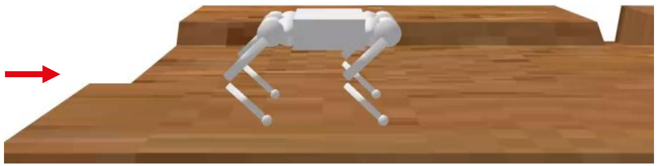


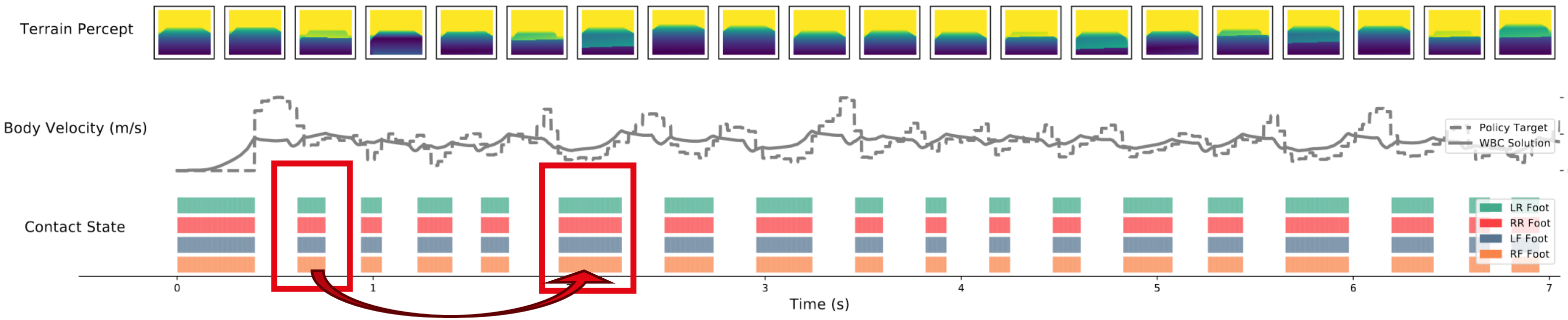
Unconstrained Gait

Max 66cm

$$C_{unconstrainted} = [\boldsymbol{a}_t^c]$$

Pronk through 65 cm gap

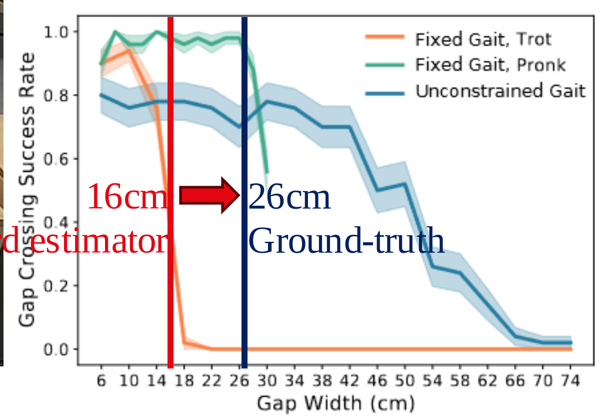




- DIC contact schedule: let policy choose contact states of each foot independently
- **Unconstrained gait policies outperform those with fixed gait, crossing gaps that are much wider.**
  - Trained with wide gaps >40cm: variable-bounding contact schedule, max 66cm
  - Trained with gap <40cm: variable-timing pronking gait

https://sites.google.com/view/jumpingfrompixels/

Results: Real World Performance



Consecutive pronking across three 15cm gaps

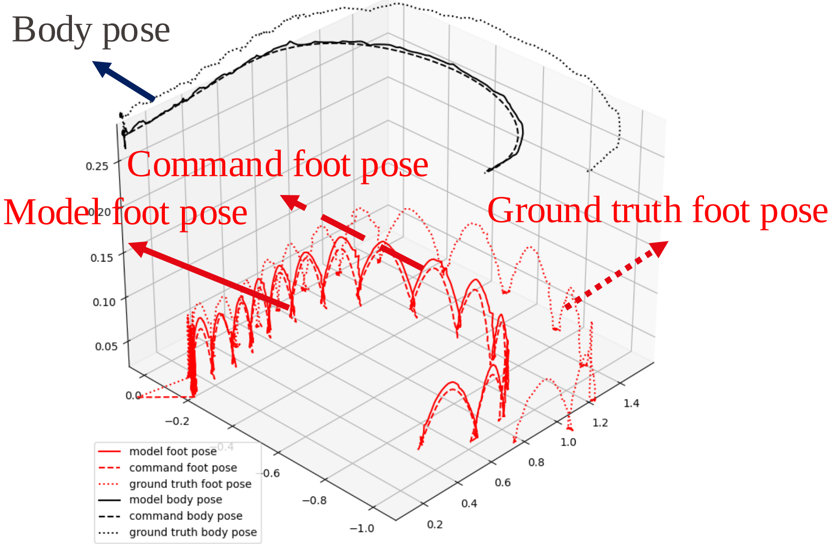
- Successful gap crossings up to **16cm** with the onboard estimator and depth images
- Able to cross gaps up to **26cm** with ground-truth state information instead of an estimator

https://sites.google.com/view/jumpingfrompixels/

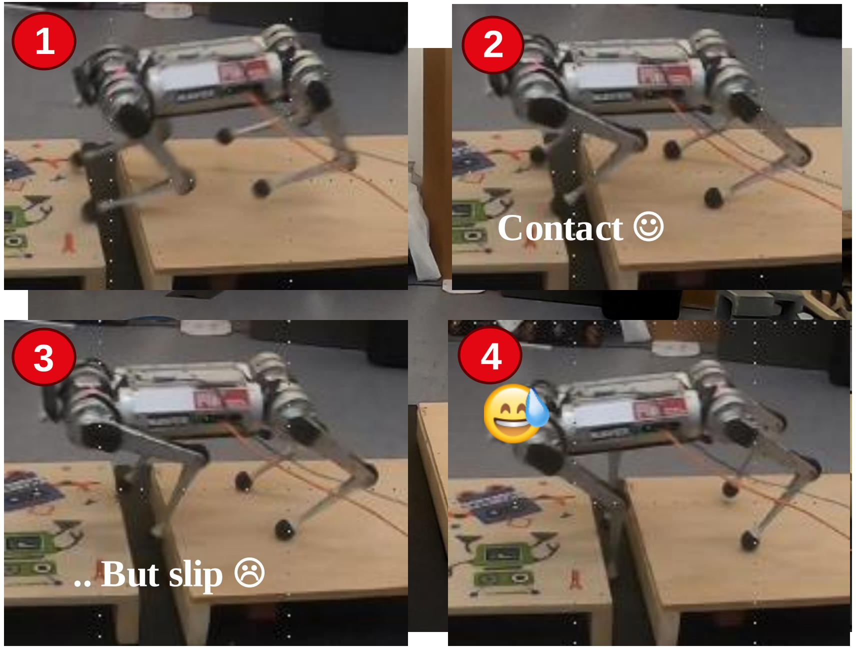
EPFL

Results: Sim-to-Real Gap

Body and foot position tracking with
onboard state estimator (IMU + Kinematics + Kalman Filter)



Feet make contact but slip due to insufficient contact force

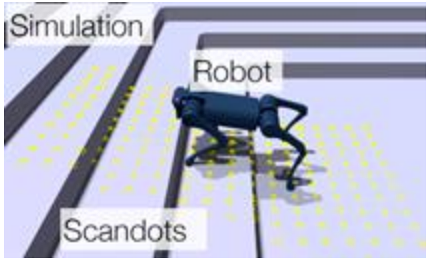


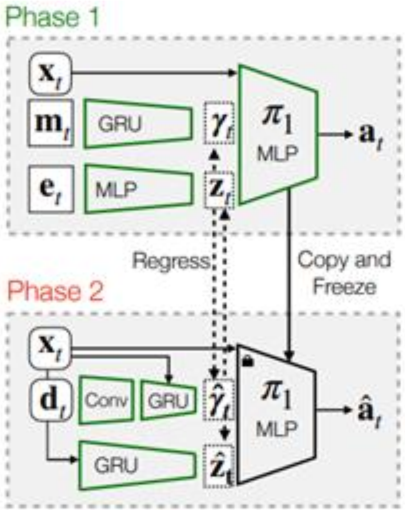
- **Drift in state estimation** caused by sensor noise and imprecise knowledge of contact timing
- Violation of the assumption made by the low-level controller that the robot’s feet do **not slip** while in contact with the floor, especially during aggressive motion.

https://sites.google.com/view/jumpingfrompixels/

Related Works

Legged Locomotion in Challenging Terrains Using Egocentric Vision (2022)



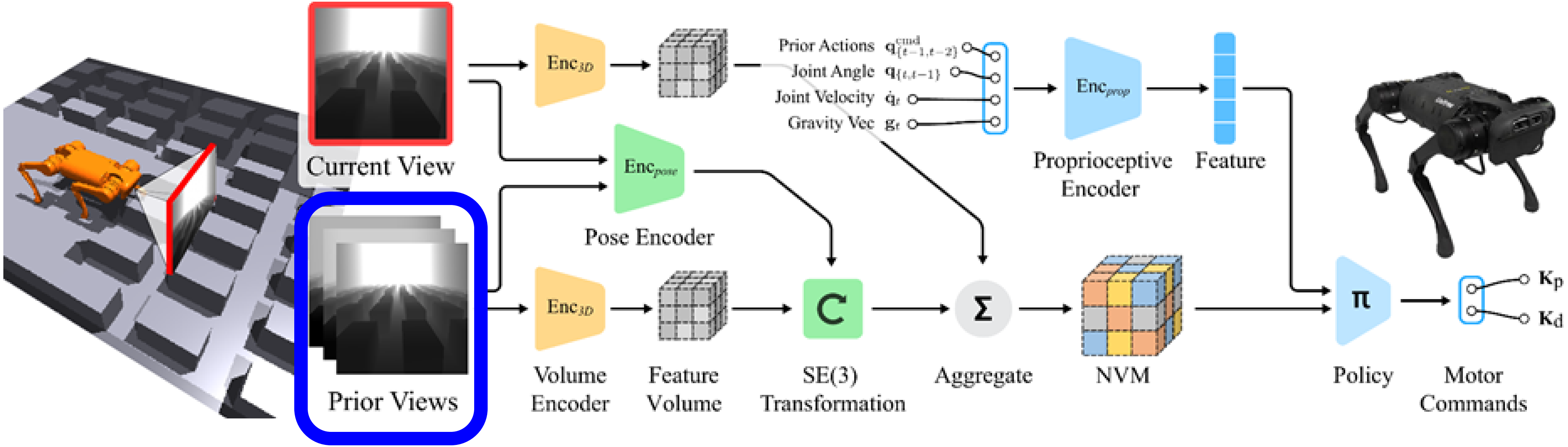


m_t = scan dots
d_t = depth graph

Directly predict target joint angles from egocentric depth without constructing metric elevation maps

Related Works

Neural Volumetric Memory (NVM) for Visual Locomotion Control (2023)



Put current **and previous** depth picture into NVM to estimate the terrain below robots

Conclusion

- **Pros:**
  - Could plan motion trajectories **in advance** based on visual information
  - **Adaptive gait**
  - Hierarchical control enables the robot to simultaneously achieve high performance and robustness

- **Cons:**
  - Assumes **no slippage** at the contact points. This discrepancy leads to low performance in real-world deployment
  - Use **only the current depth graph**, so robot just get the front information
  - Cannot deal with **drift** in state estimation

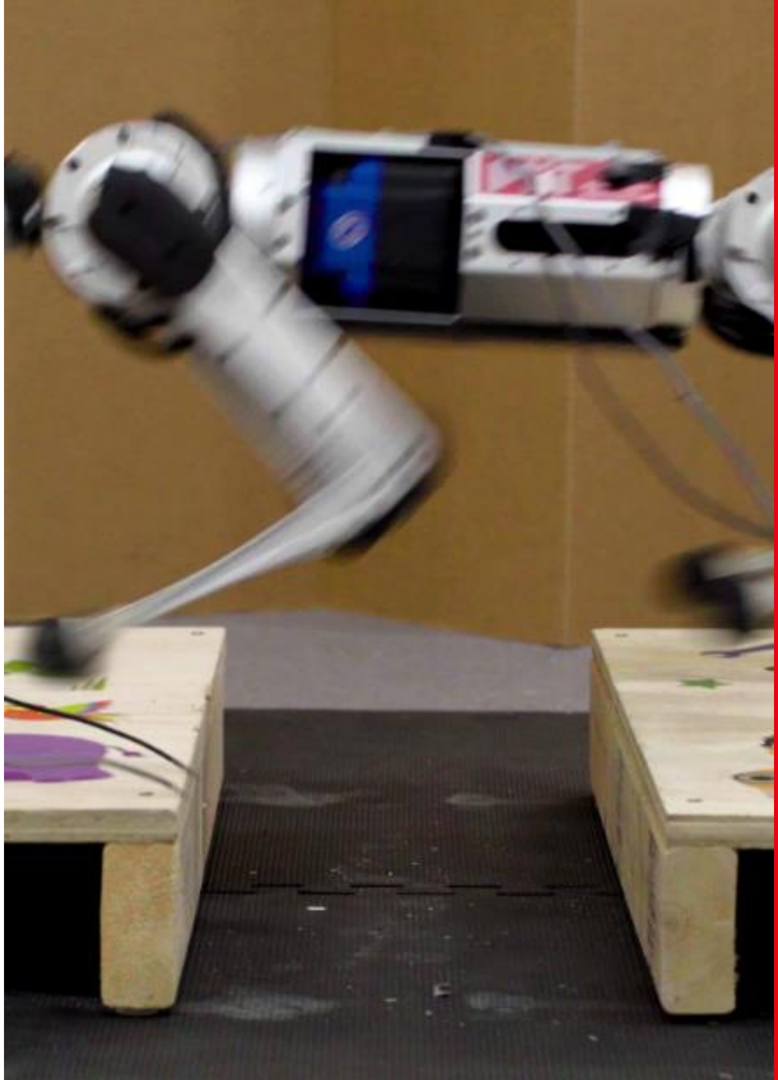
Possible exam questions

1. What is Depth Based Impulse Control (DIC), and how does it enable a robot to perform agile movements like jumping? (Answer on slides 3-5)

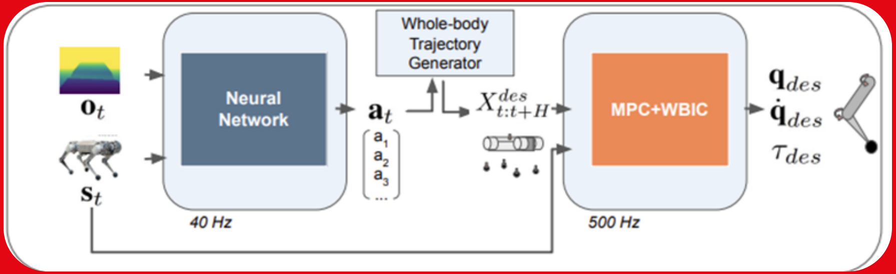
2. What caused the huge sim-to-real gap when deploying the Depth-based Impulse Control (DIC) with onboard state estimator? (Refer to slide 10)

Bibliography

- Margolis, Gabriel B., et al. "Learning to jump from pixels." *arXiv preprint arXiv:2110.15344* (2021).
- Project web: https://sites.google.com/view/jumpingfrompixels/
- Agarwal, Ananye, et al. "Legged locomotion in challenging terrains using egocentric vision." *Conference on robot learning*. PMLR, 2023.
- Yang, Ruihan, Ge Yang, and Xiaolong Wang. "Neural volumetric memory for visual locomotion control." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2023.



Thank you



- Quadruped robot
- Depth-based Impulse Control (DIC)
  - Learning-based control
  - Model-based control
- Adaptive gait
- Depth camera