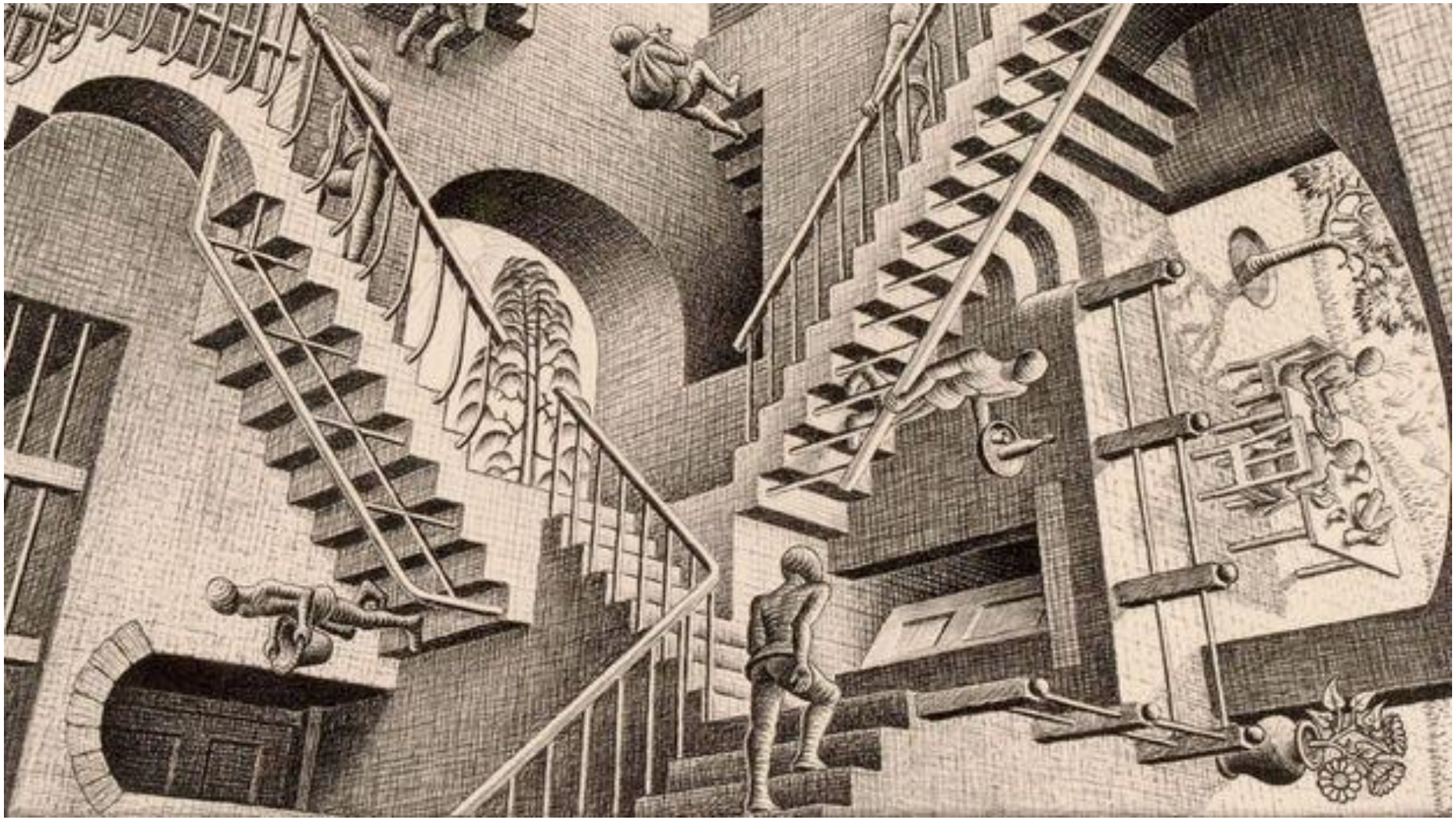
A Gentle Intro to Sim2Real

ESE 6510
Antonio Loquercio

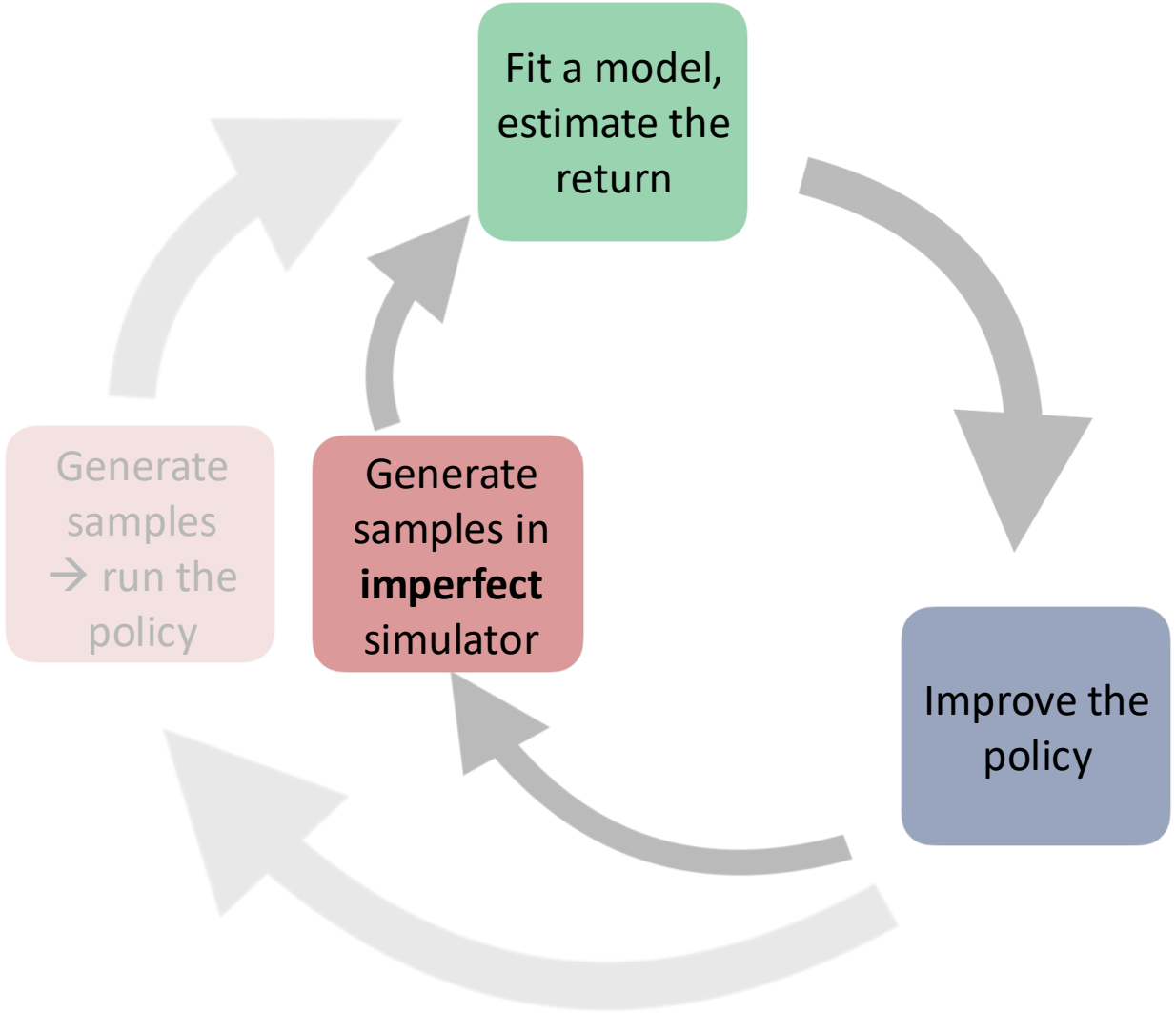


M.C. Escher,

***Relativity*, 1953**

What is Sim2Real?

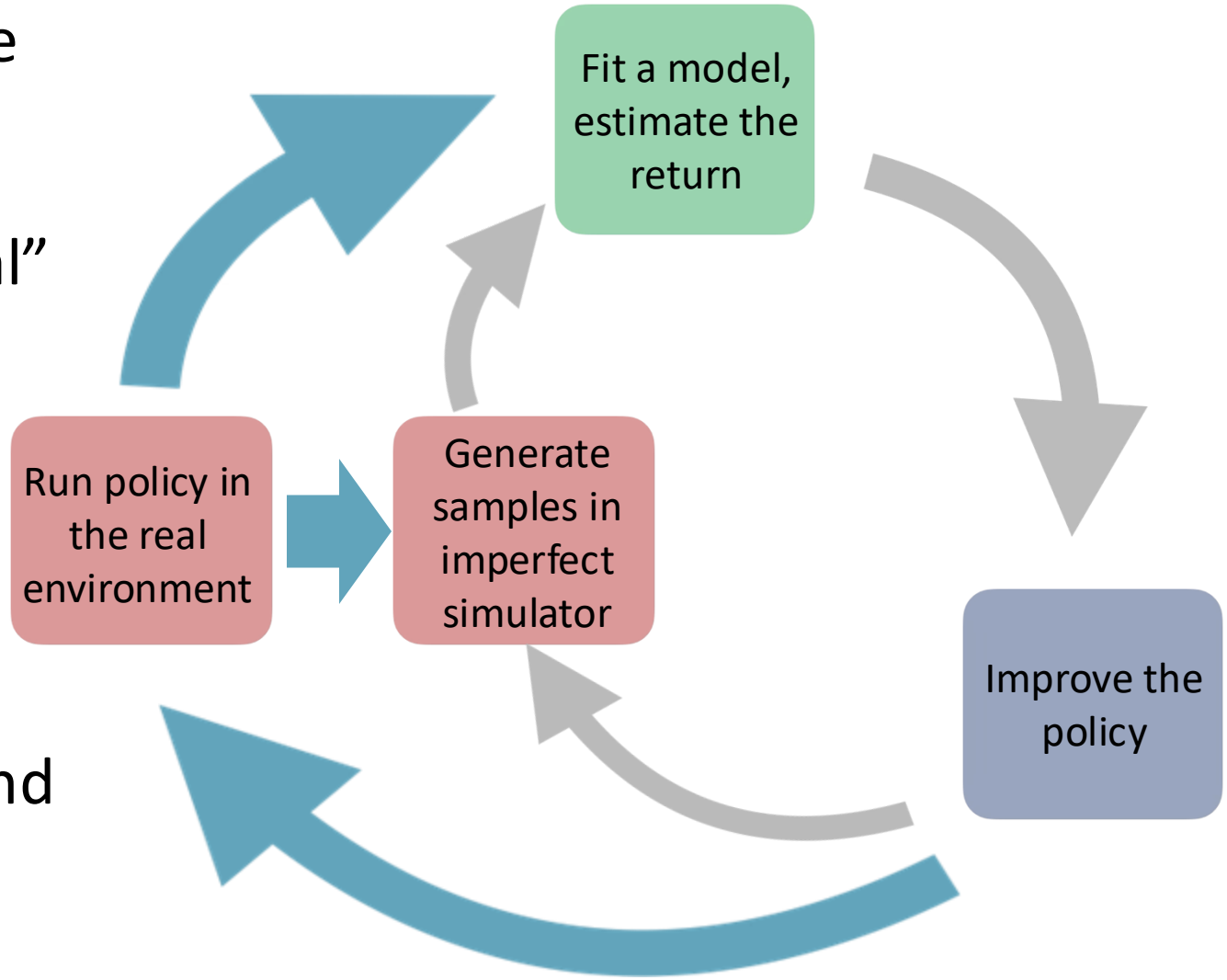
A family of methods that enable policies trained in an **imperfect world model** to successfully transfer and operate in the “real” environment.



What is Sim2Real?

A family of methods that enable policies trained in an **imperfect world model** to successfully transfer and operate in the “real” environment.

Evaluations of the policy in the real environment are used to **improve** both the **simulation** and the **policy learning** approach.



The Simulation to Reality Gap(s)

- Dynamics gap:

$$s_{t+1} = f_{real}(s_t, a_t) \neq f_{sim}\,(s_t, a_t)$$

- Sensory gap:

$$\mathrm{o_t} = obs_{real}(s_t) \neq obs_{sim}(s_t)$$

- Semantic (or Environment) gap:
  - Things should have the right size relatively to each other and placed where it makes sense.
  - Other agents should behave in a way that is realistic.

Categories of Sim2Real Algorithms

- Domain Randomization
  - Naïve
  - Adaptive
  - Physics-based
- Adaptive Control
  - Explicit System Identification
  - Implicit System Identification
- Abstractions-based
  - Visual Abstractions
  - Control Abstractions

Most papers use a mix of these techniques. But some applications require care.

How to pick the parameters distribution?

- Naïve
- Performance-based (Adaptive)
- Physics-based

How to pick the parameters distribution?

- Naïve: Select the subspace of parameters you are the most uncertain about. Fix the ones you know.

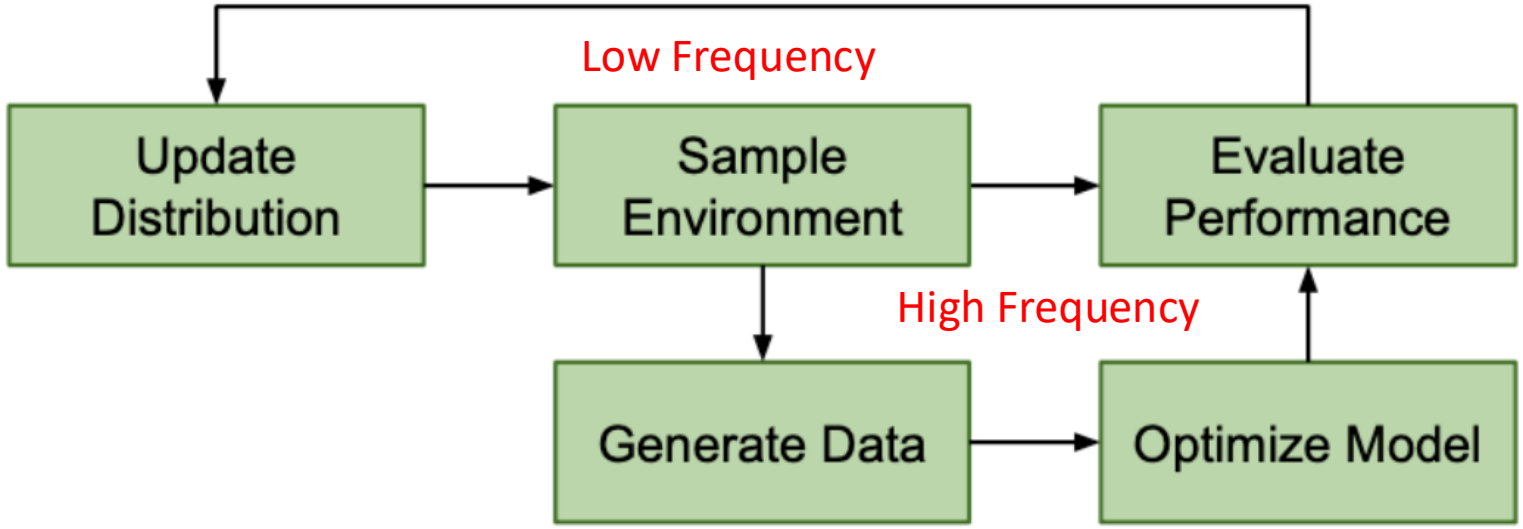
- If no prior information is available, use a uniform distribution over the range of parameters.

Limitations?

- Compute intensive/challenging to converge if the ranges are large.
- Some combinations of parameters potentially make no sense; why train on them?

How to pick the parameters distribution?

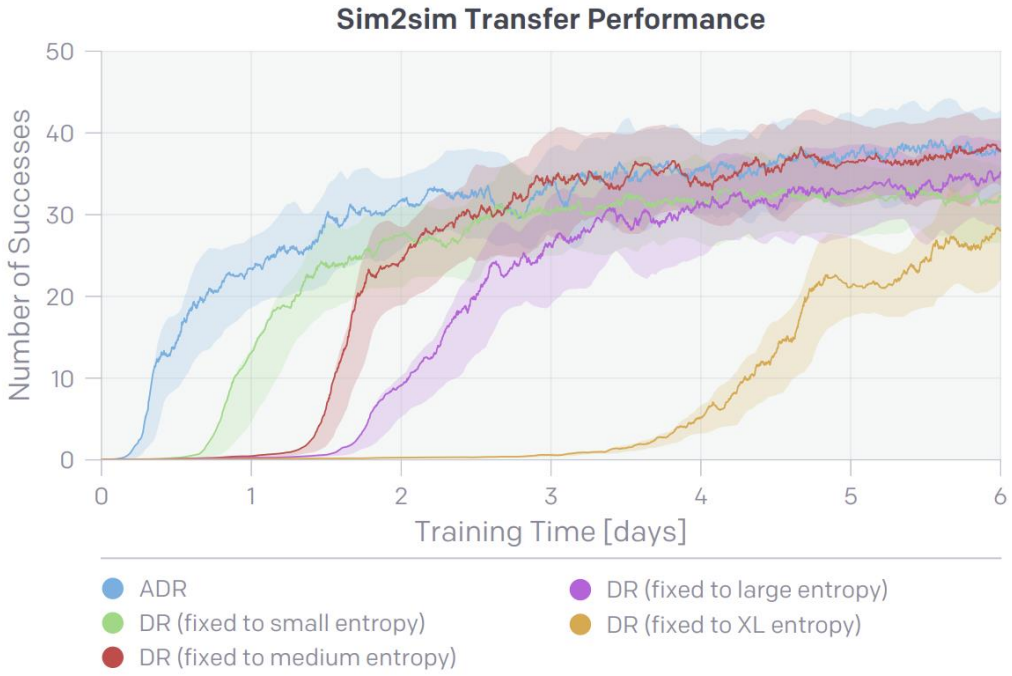
- Performance-based (adaptive): Gradually adapt the ranges to make the agent never too successful or unsuccessful: Curriculum-like.

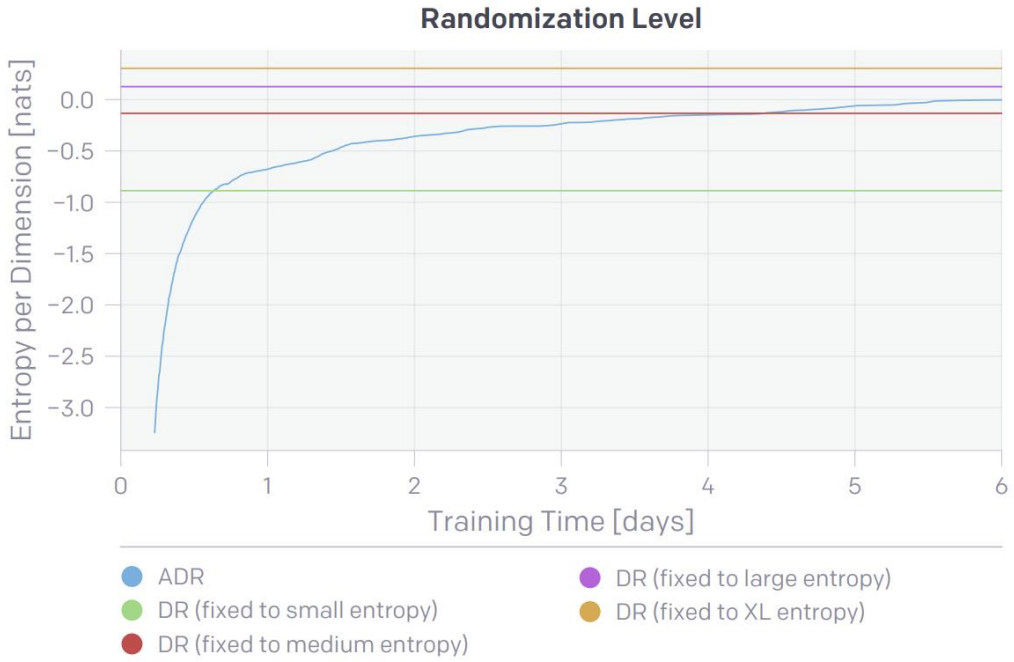


- Popularized by OpenAI's Rubik's Cube paper (https://openai.com/index/solving-rubiks-cube/)

How to pick the parameters distribution?

- Performance-based (adaptive): Faster to converge than traditional DR





Solving Rubik's Cube with a Robot Hand, 2019

How to pick the parameters distribution?

- Performance-based (adaptive): Can train on larger ranges and therefore transfer better (note: comparison not 100% fair).

Policy	Training Time	ADR Entropy	Successes (Sim)		Successes (Real)	
			Mean	Median	Mean	Median
Baseline (data from [77])	—	—	43.4 ± 0.6	**50**	18.8 ± 5.4	13.0
Baseline (re-run of [77])	—	—	33.8 ± 0.9	**50**	4.0 ± 1.7	2.0
Manual DR	13.78 days	-0.348^{*} npd	42.5 ± 0.7	**50**	2.7 ± 1.1	1.0
ADR (Small)	0.64 days	-0.881 npd	21.0 ± 0.8	15	1.4 ± 0.9	0.5
ADR (Medium)	4.37 days	-0.135 npd	34.4 ± 0.9	**50**	3.2 ± 1.2	2.0
ADR (Large)	13.76 days	0.126 npd	40.5 ± 0.7	**50**	13.3 ± 3.6	11.5
ADR (XL)	—	0.305 npd	45.0 ± 0.6	**50**	16.0 ± 4.0	12.5
ADR (XXL)	—	**0.393 npd**	$\mathbf{46.7 \pm 0.5}$	**50**	$\mathbf{32.0 \pm 6.4}$	**42.0**

Solving Rubik's Cube with a Robot Hand, 2019

How to pick the parameters distribution?

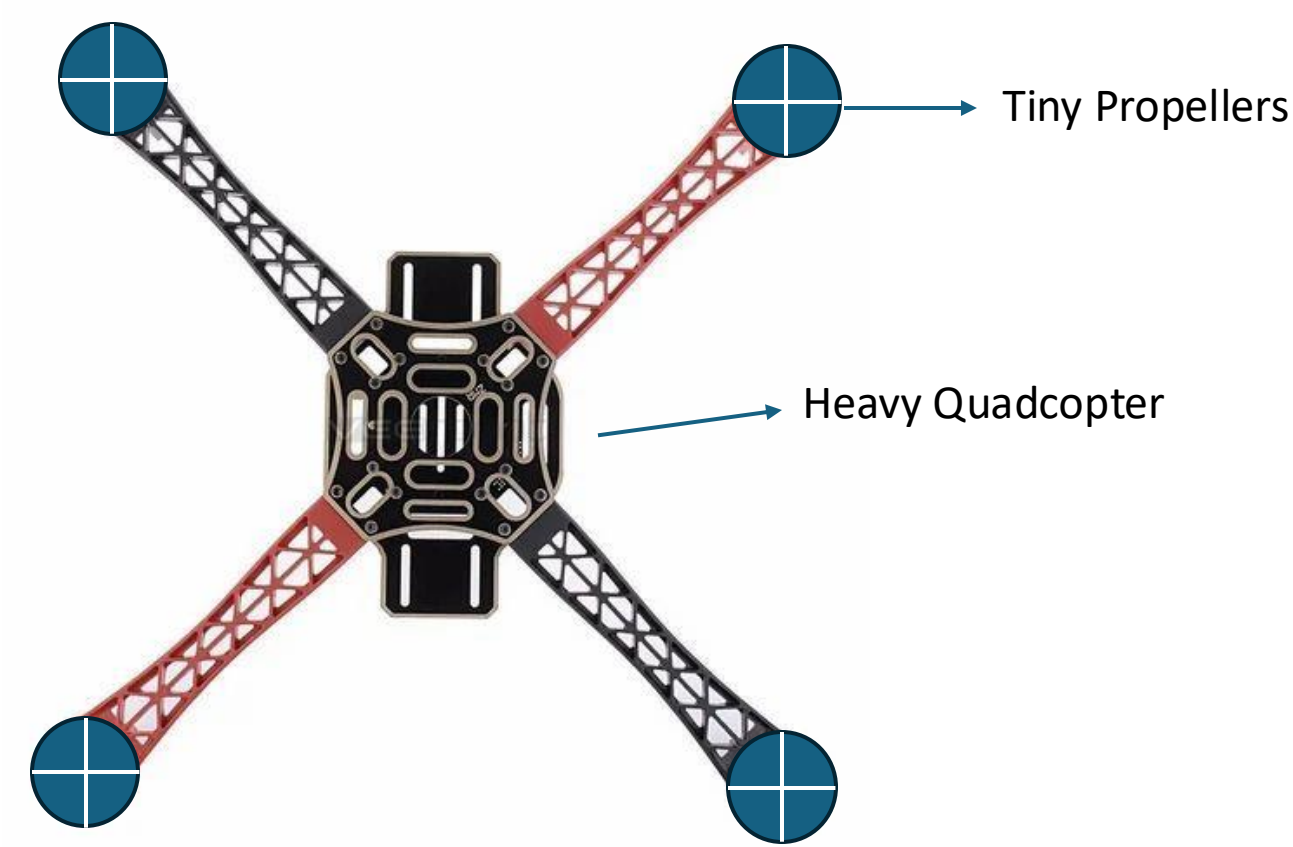
- Performance-based (adaptive): Not very much used in practice (but I have seen some good recent papers using it).

- Limitations?

- Many more hyperparameters beyond the ranges
  - Success/Failure thresholds, minimum waiting time, delta update, …
- To some extent, this happens already if you train with massively parallel environments:
  - At the beginning of training, the batch will be full of “easy” parameters but later it will balance.

How to pick the parameters distribution?

- Physics-based: Use prior knowledge about the system to generate parameter combinations that are physically plausible.
- Why train on this?



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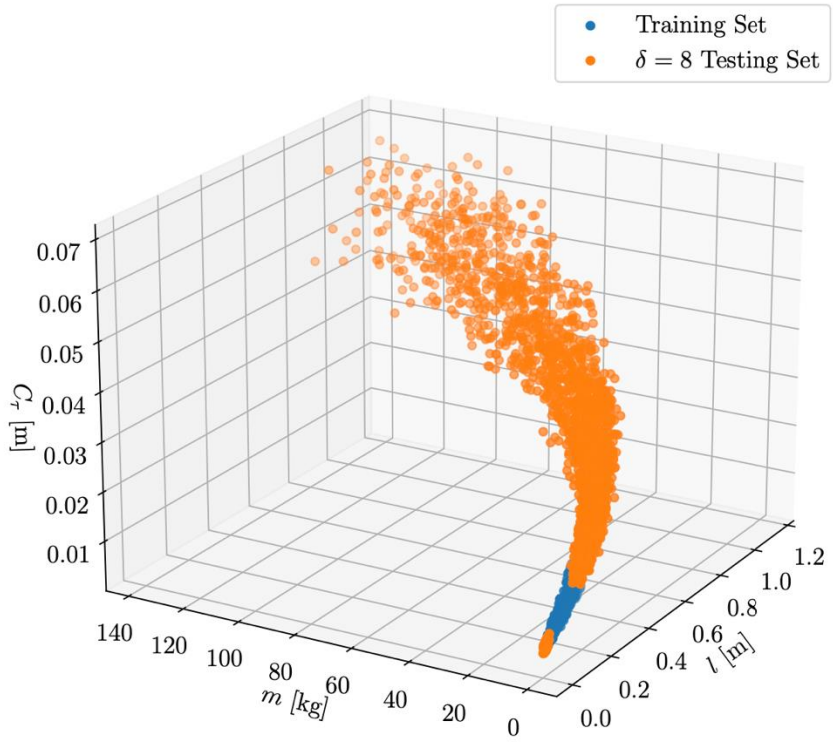
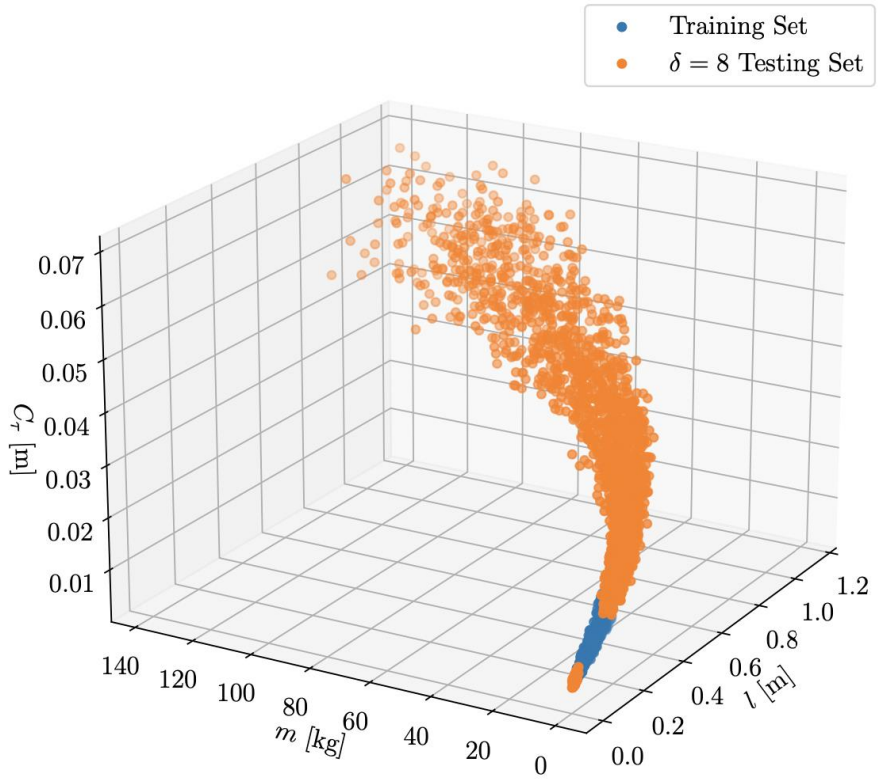
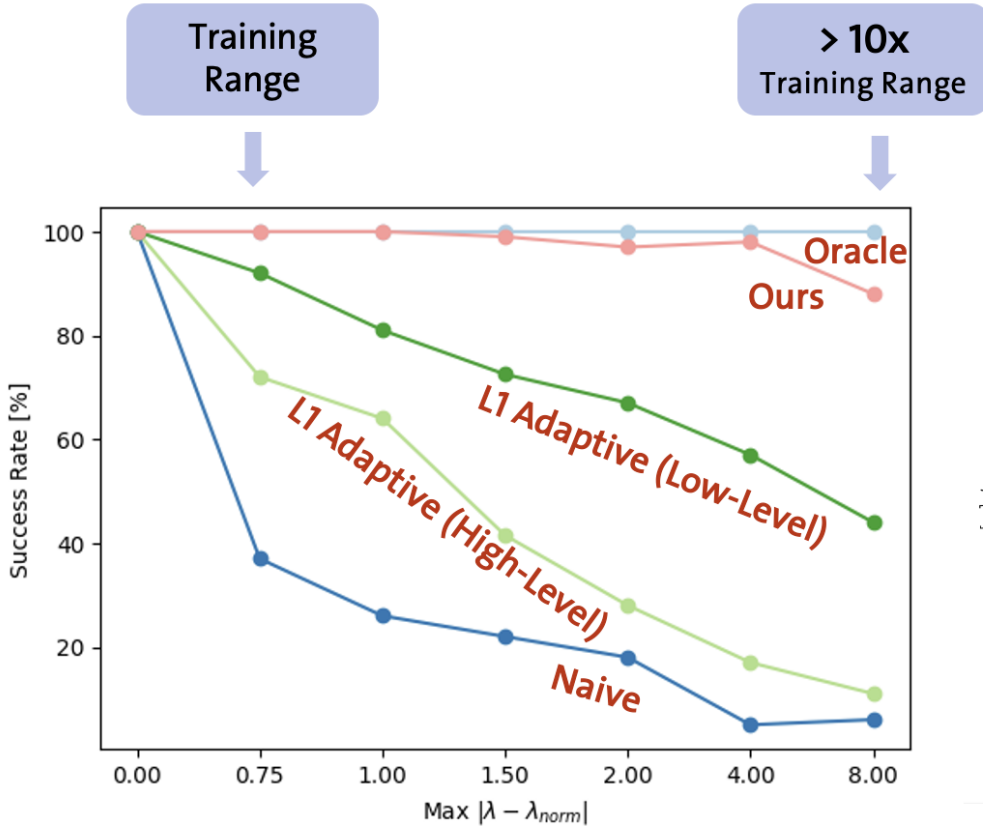


A Learning-based Quadcopter Controller with Extreme Adaptation, 2025

How to pick the parameters distribution?

- **Interesting (but problem-specific) finding.** Physics-based randomization enables generalization beyond the training range.





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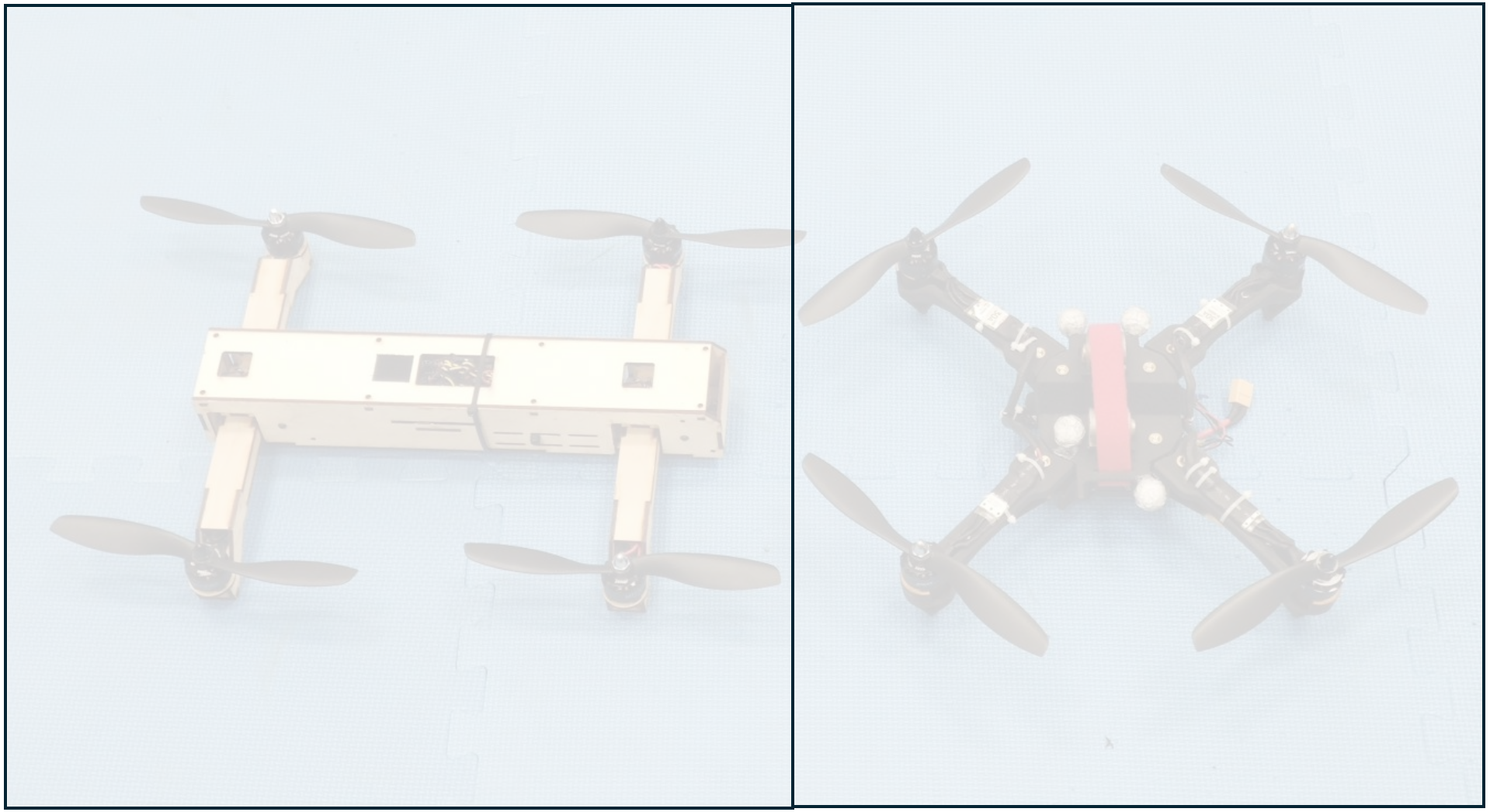
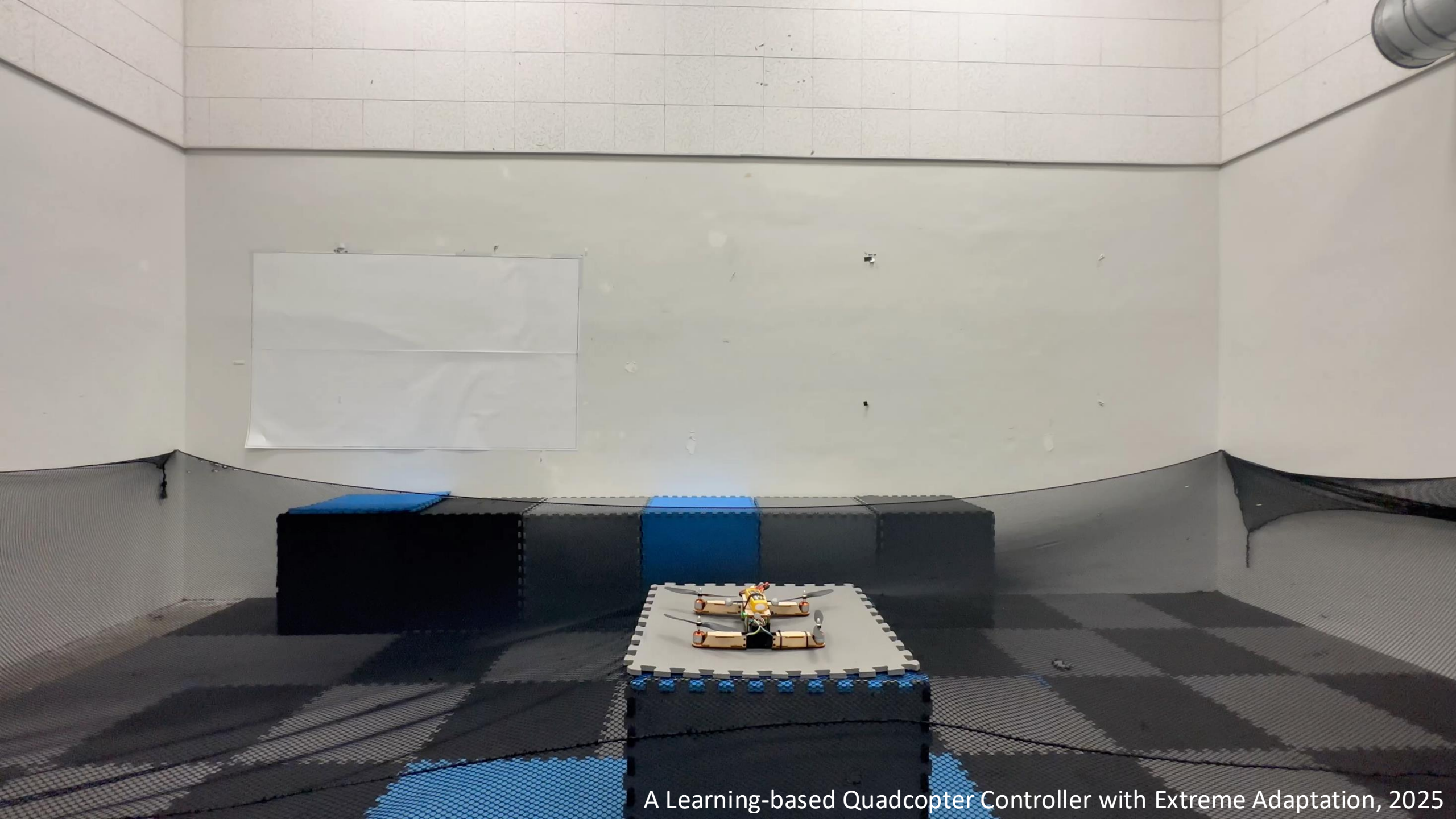
Flying Different Morphologies



QUaRTM: A Quadcopter with Unactuated Rotor Tilting Mechanism Capable of Faster, More Agile, and More Efficient Flight, Jerry Tang, Karan P. Jain, and Mark W. Mueller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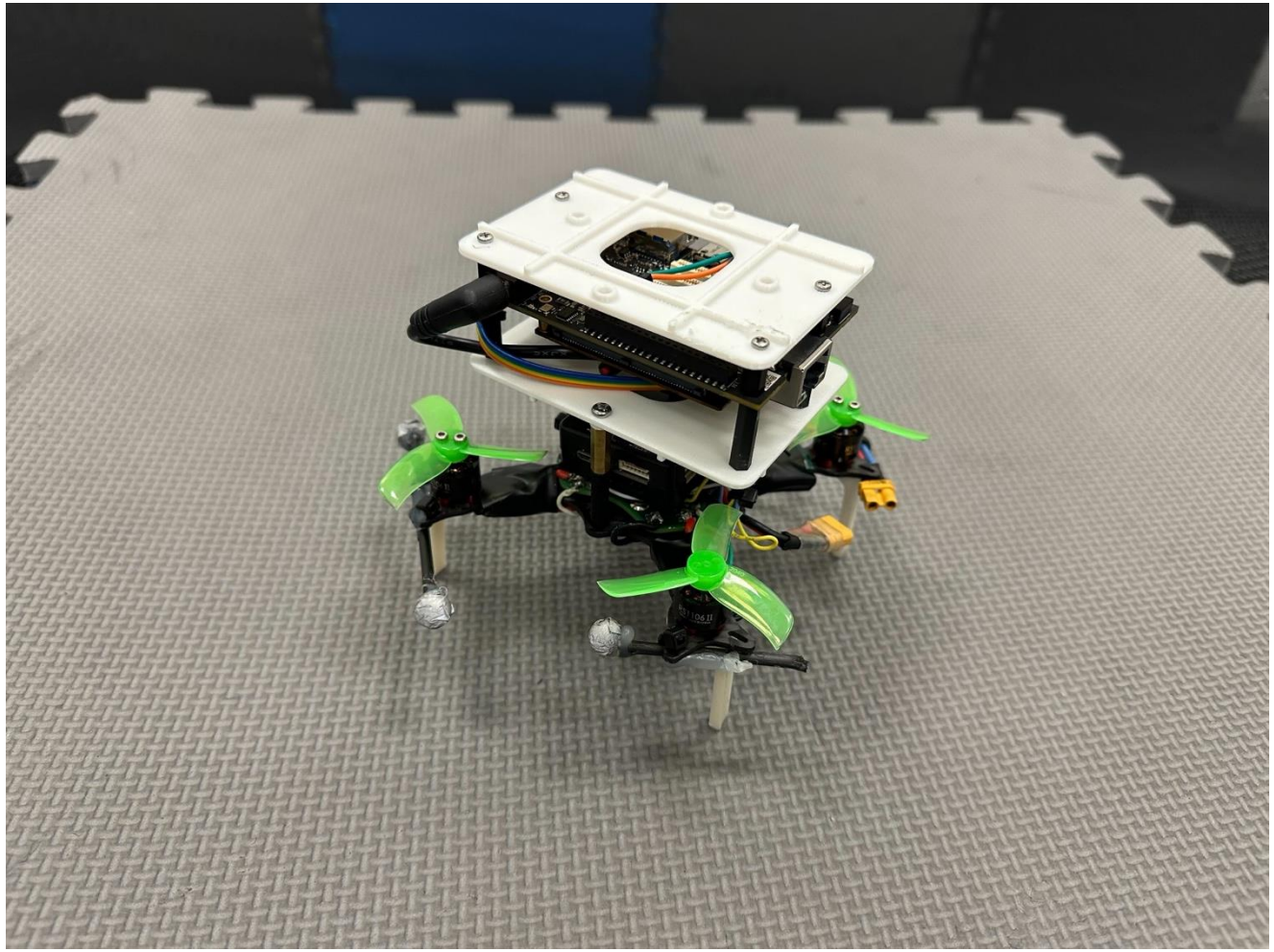
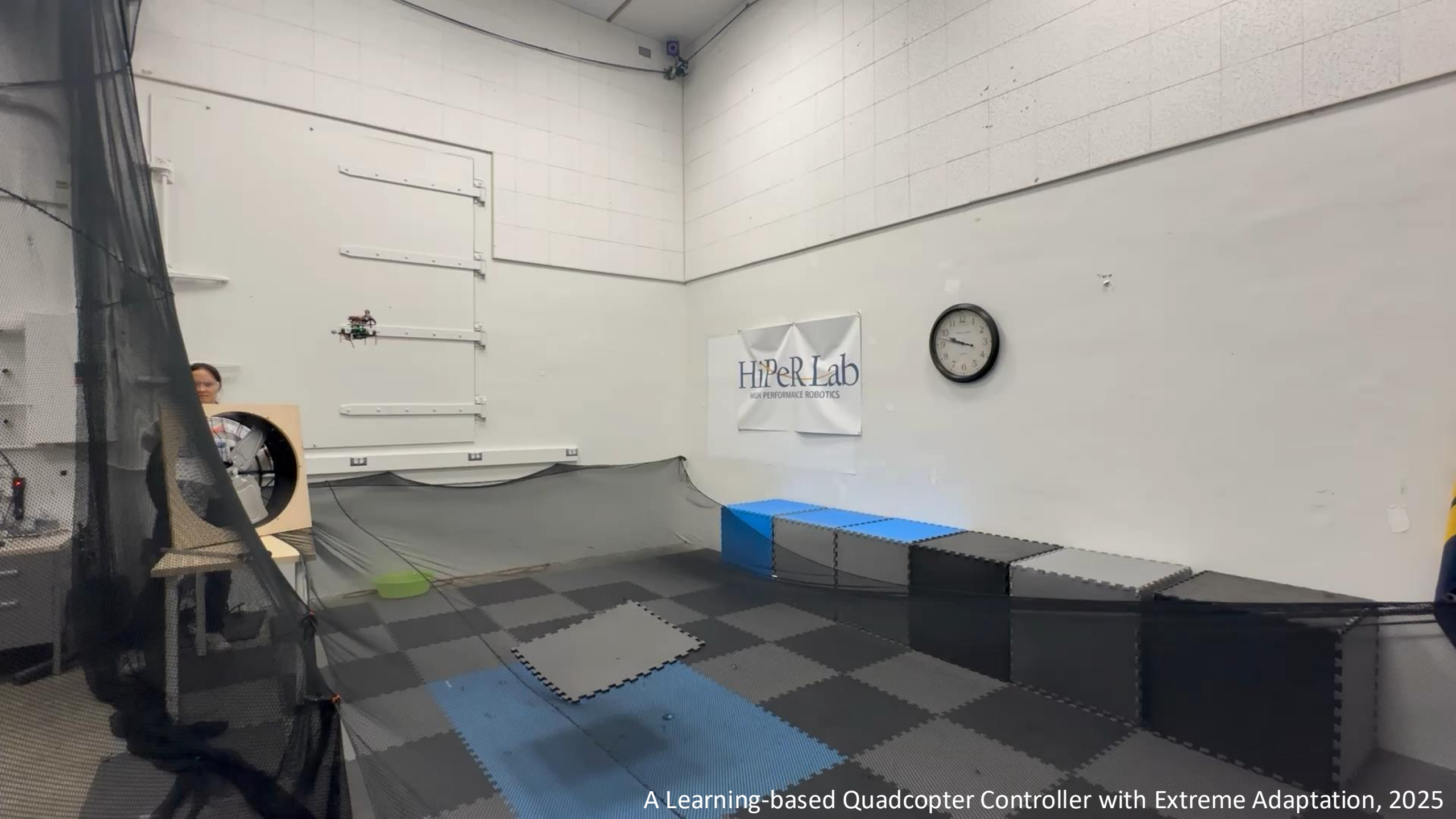
Flying Different Morphologies



- ~30% mass above the propellers
- 3X larger x-z inertia than a normal drone.

A Learning-based Quadcopter Controller with Extreme Adaptation, 2025



A Learning-based Quadcopter Controller with Extreme Adaptation, 2025

How to pick the parameters distribution?

- Physics-based: Use prior knowledge about the system to generate parameter combinations that are physically plausible.

- Limitations?

- Unclear how to design these relationships for complex systems (e.g., a dexterous hand).
- Unclear how to apply this for sensory and semantic randomization.

Why does domain randomization work? (Disclaimer: Opinion)

- Let's go back to the optimization objective of domain randomization

$$\theta^* = argmax_\theta \, \mathbb{E}_{e \sim D}[\, C(\theta, e)]$$

- A good solution to this problem is learning to quickly learn/adapt.
- For example, the agent can learn how to do quick estimation of parameters and learn the relation between parameters and actions (e.g., the larger the mass, the larger the force).
- This does not require that the real world is in the simplex of the parameter ranges.
- Can we design algorithms to bias the agent to learn this behavior?

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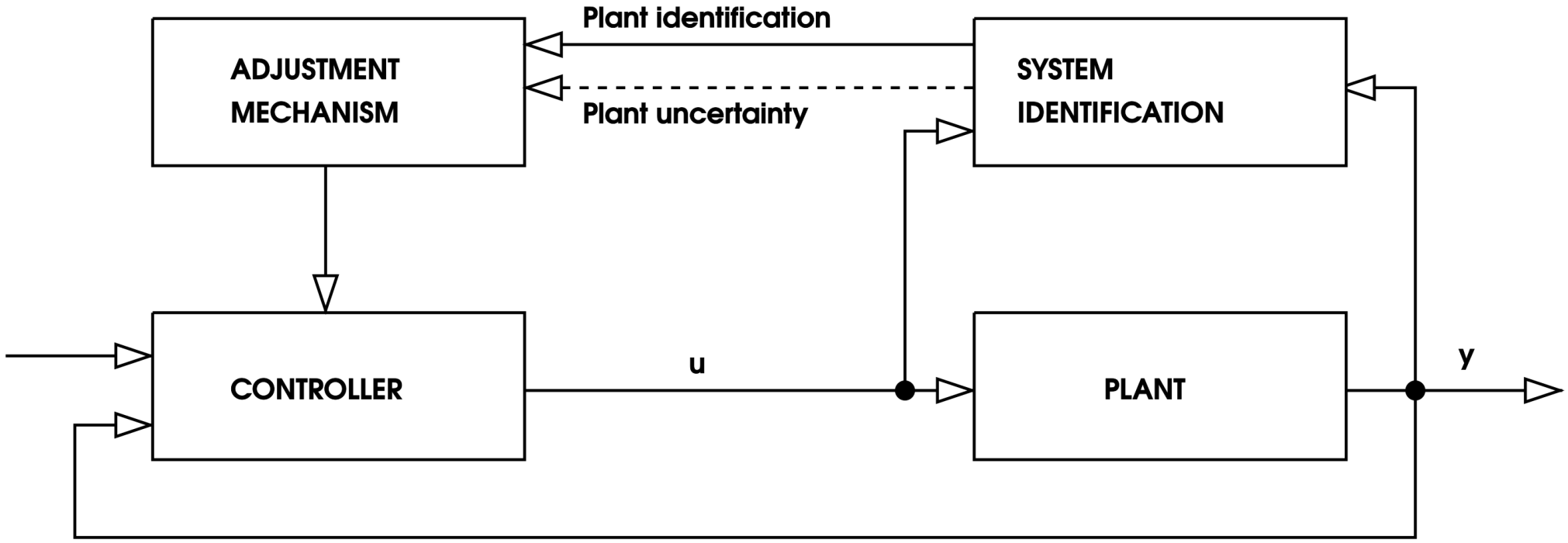
Adaptive Control

- **Key Idea**: Identify the parameters of the system from (possibly limited) on-policy experience. Condition or finetune the policy on the estimated parameters.



MODEL IDENTIFICATION ADAPTIVE CONTROL (MIAC)

Source: Wikipedia

Adaptive Control

Two types of adaptive sim2real:

- **Explicit parameter estimation (Real-to-Sim)**: find the actual parameters.

- **Implicit parameter estimation:** find a compressed representation of the parameters.

Some methods do a hybrid of these two (identify what is fixed, adapt to things that change).

Adaptive Control: Explicit Parameter Estimation

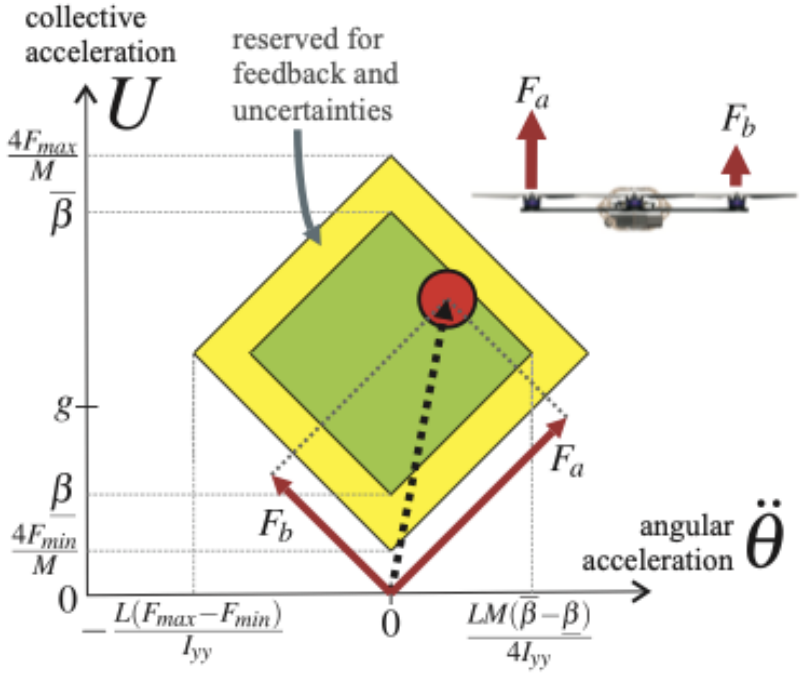
A Simple Learning Strategy for High-Speed Quadrocopter Multi-Flips

Sergei Lupashin, Angela Schöllig, Michael Sherback, Raffaello D'Andrea

ICRA, 2010

Adaptive Control: Explicit Parameter Estimation

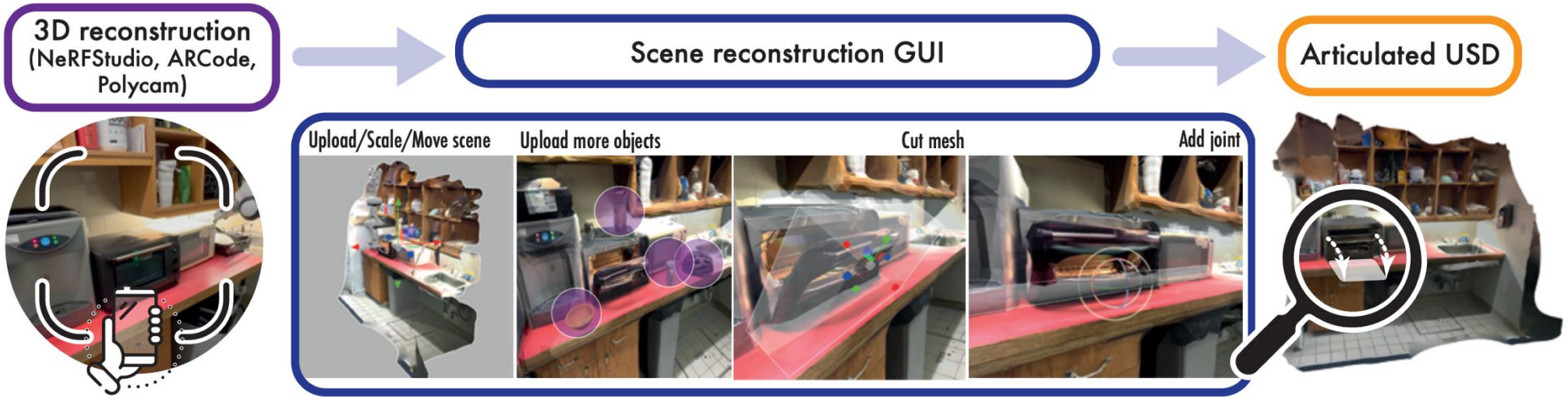
- Estimation is never perfect: uncertainty in some parameters always remains.
- To account for this, explicit identification is generally coupled with domain randomization.



A Simple Learning Strategy for High-Speed Quadcopter Multi-Flips, 2010

Adaptive Control: Explicit Parameter Estimation

Modern take to the problem: estimate not only physical parameters, but the whole scene.



Reconciling Reality through Simulation: A Real-to-Sim-to-Real Approach for Robust Manipulation, 2024

Adaptive Control: Explicit Parameter Estimation

Modern take on the problem: estimate not only physical parameters, but the whole scene.

Limitations of scene-level real-to-sim?

- The more complex the scene, the slower the simulation.
- Articulation of objects is non-trivial when done for more than a handful of objects (particularly hard for deformable objects).
- Reconstruction artifacts might impact the behavior of the policy. Policies are generally finetuned, not trained from scratch.

However, we don’t (yet) have better methods to cope with the semantic sim2real gap!

Adaptive Control

- **Explicit parameter estimation (Real-to-Sim)**: find the actual parameters.

- Limitations?

- Some parameters might not be identifiable given some limited on-policy experience.
- Multiple parameters might explain the same behavior. Which one to pick?
- We might not really need the parameters by themselves, only their relation to the task.

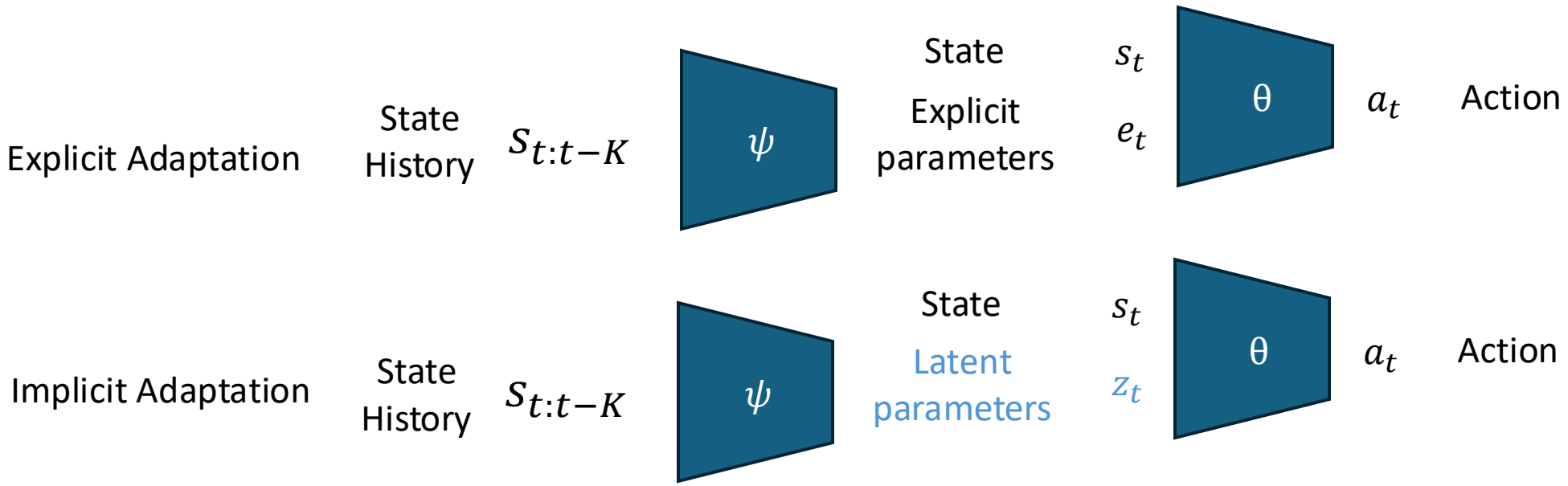
Adaptive Control

- **Implicit parameter estimation:** find a compressed representation of the parameters.

- **Key insights**:
  - *Parameters cannot be uniquely identified*.
    Example: in drones, we can estimate the thrust-to-weight ratio, but not the exact mass and thrust.
  - *Parameters that cannot be uniquely identified are not necessary for my downstream task*.
    Example: If I only care about controlling the drone's acceleration, the actual mass and thrust are not important.

Adaptive Control

- **Implicit parameter estimation:** find a compressed representation of the parameters.
- The origins of these techniques are in the adaptive control literature for linear systems (implicit adaptive control).
- More recently adapted to learning-based approaches and sim2real.



Latent-Based Identification.

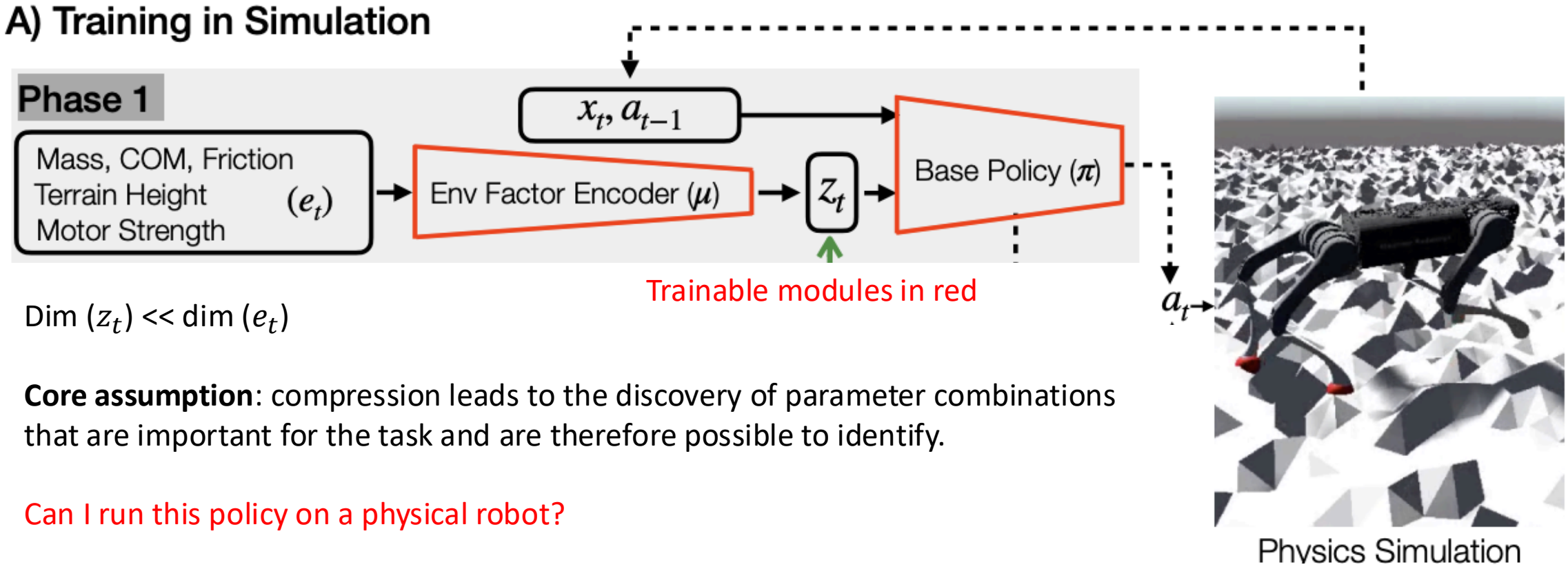
Core question: how to identify the parameters combination that can be identified and are important for the task?

Possible answer: Learn it from data by training a highly compressed latent representation of the parameters.

Initially proposed by:

1. Learning Quadrupedal Locomotion over Challenging Terrain, Lee et al., 2020
2. Rapid Motor Adaptation, Kumar et al., 2021

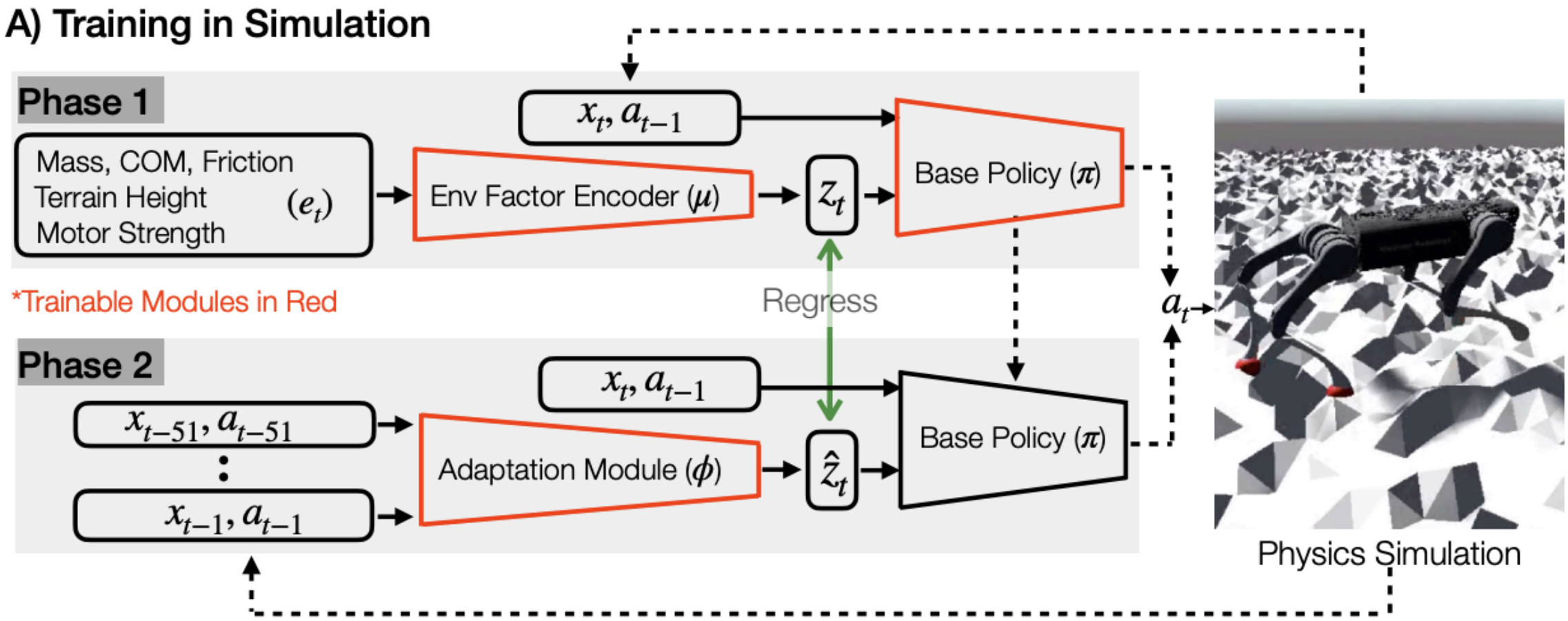
Rapid Motor Adaptation



Trainable modules in red

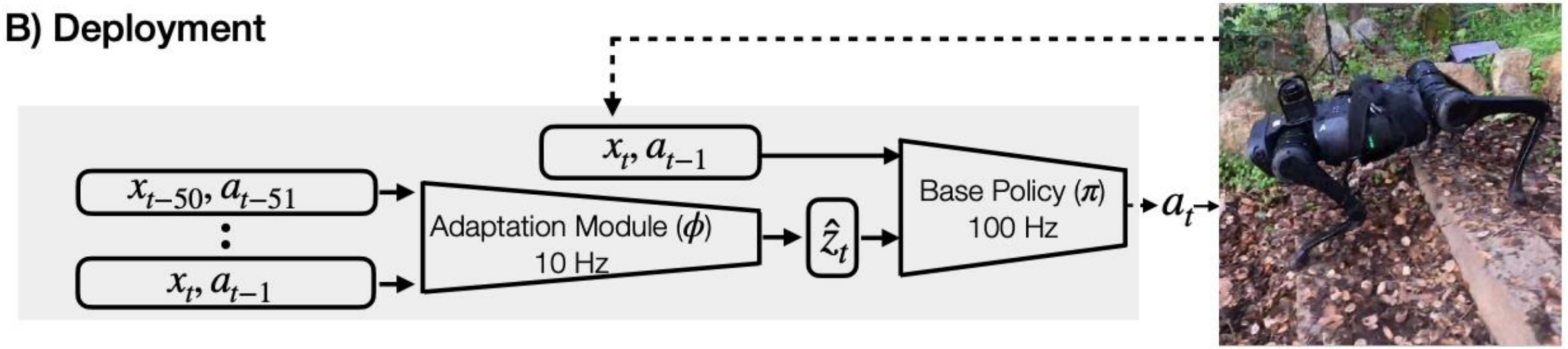
- Dim (z_t) << dim (e_t)
- **Core assumption**: compression leads to the discovery of parameter combinations that are important for the task and are therefore possible to identify.
- Can I run this policy on a physical robot?

Rapid Motor Adaptation



- The history of previous actions and states is used for predicting the latent representation of parameters.
- The action policy is kept frozen (in some implementations)

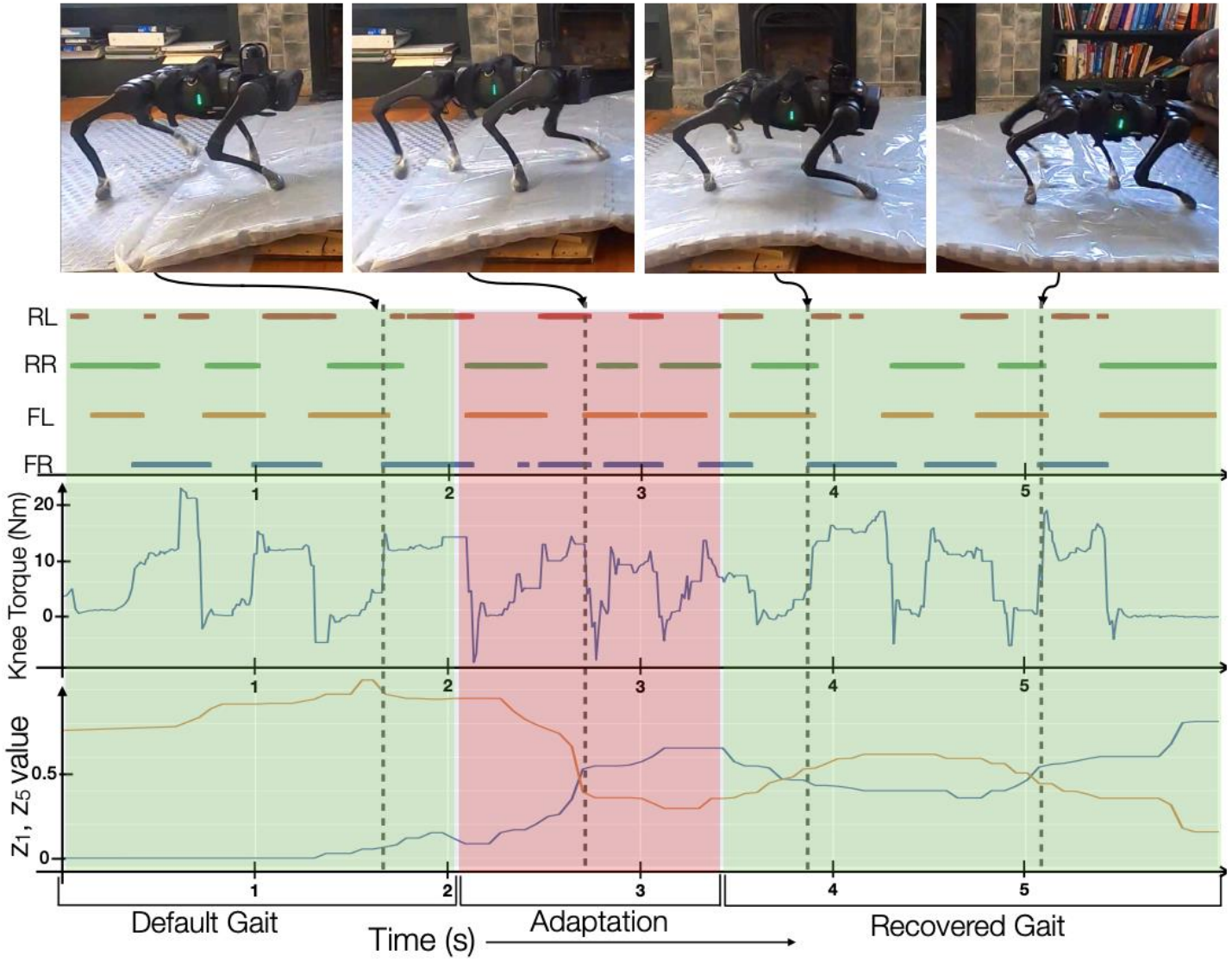
Rapid Motor Adaptation



- The adaptation module and policy can be deployed zero-shot on the robot.
- Strong performance in environments not modeled at training time (e.g., sand, stairs, foliage)

Quick Adaptation

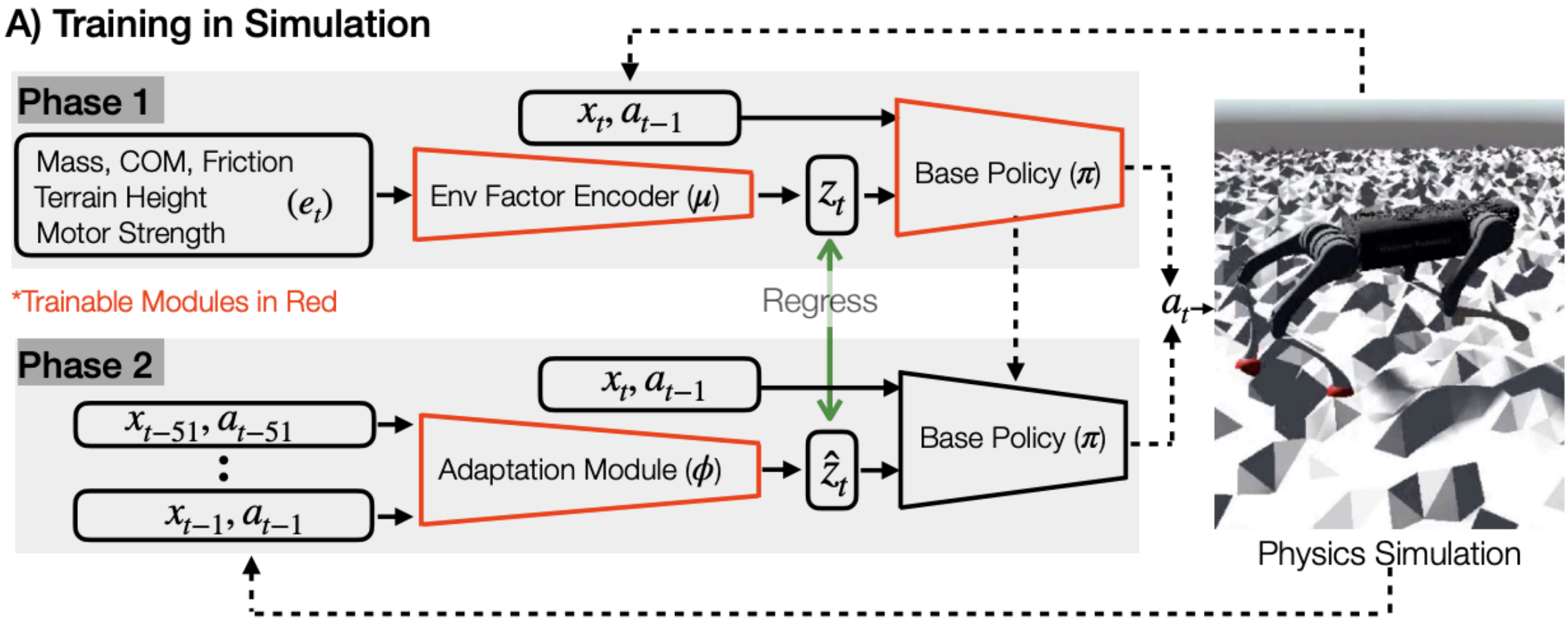
Quick Adaptation



The approach has been applied to many locomotion problems

- Parkour
  - Examples:
    - Parkour in the wild: Learning a general and extensible agile locomotion policy using multi-expert distillation and RL Fine-tuning, Rudin et al. 2025
    - Extreme Parkour with Legged Robots, Cheng et al., 2024
    - Robot Parkour Learning, Zhuang et al., 2023
- Vision-based locomotion
  - Examples:
    - Legged Locomotion in Challenging Terrains using Egocentric Vision, Agarwal et al, 2022
    - Learning robust perceptive locomotion for quadrupedal robots in the wild, Miki et al, 2022
- General takeaway:
  - The more challenging the task is, the more tricks are required (several RL experts, curriculum on contacts models, tailored perception systems).
  - The approach does not simply scale.

Rapid Motor Adaptation



- Limitations?

Limitations and How to (partially) address them

- The compression objective could not be sufficient to achieve the goal of predictability.
  - Add an extra objective during phase I training which focuses on predictability
  - Example:
    - Deep Whole-Body Control: Learning a Unified Policy for Manipulation and Locomotion, Fu et al. 2022.
- The base policy should potentially change its behavior when it does not observe the ground truth parameters.
  - Fine-tune the base policy together with the adaptation module with RL.
  - Examples:
    - Adapting Rapid Motor Adaptation for Bipedal Robots. Kumar et al., 2022

- A two-stage procedure is cumbersome. Errors can compound between phases.
  - Recent work seems to prefer the reward/observation engineering route

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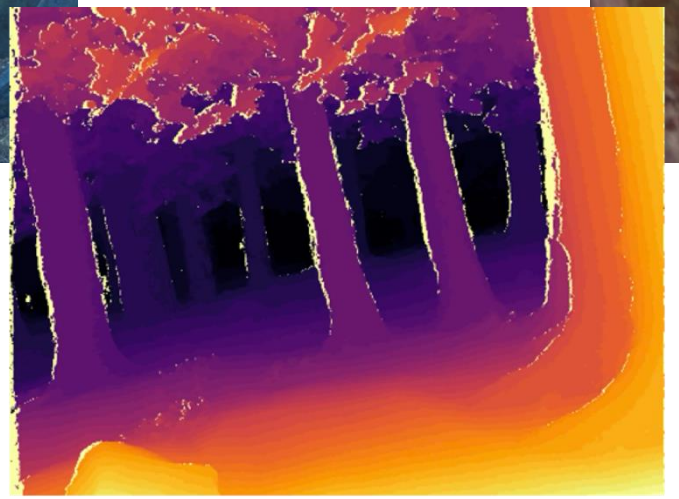
Abstraction-based Sim2Real

General idea: train the policy on *curated* sensory/control abstractions that reduce the gap between simulation and real world.



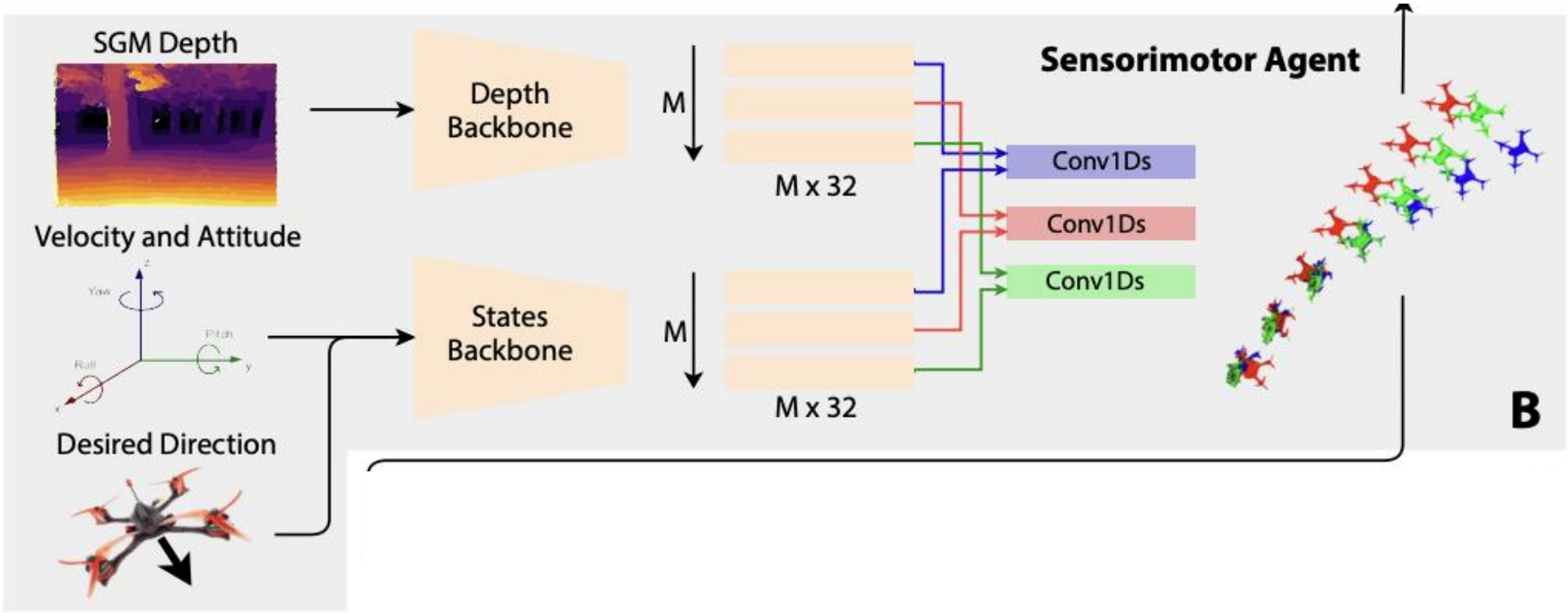
Examples of Sensory Abstractions

- Gate Detection in drone racing
- Pose estimation and mapping for navigation
- 6D Object Pose detection for manipulation
- Many others (each problem can have its own simulation engineering)

Control Abstractions

- Low-level controllers (e.g., MPC) can track trajectories or joint positions, so that the policy can focus on higher-level control.
  - Paradoxically, this could potentially lead to an increased sim2real gap if the low-level controller does not behave similarly in simulation and the real world.
  - Randomization becomes harder to do (need to make the low-level adaptive)

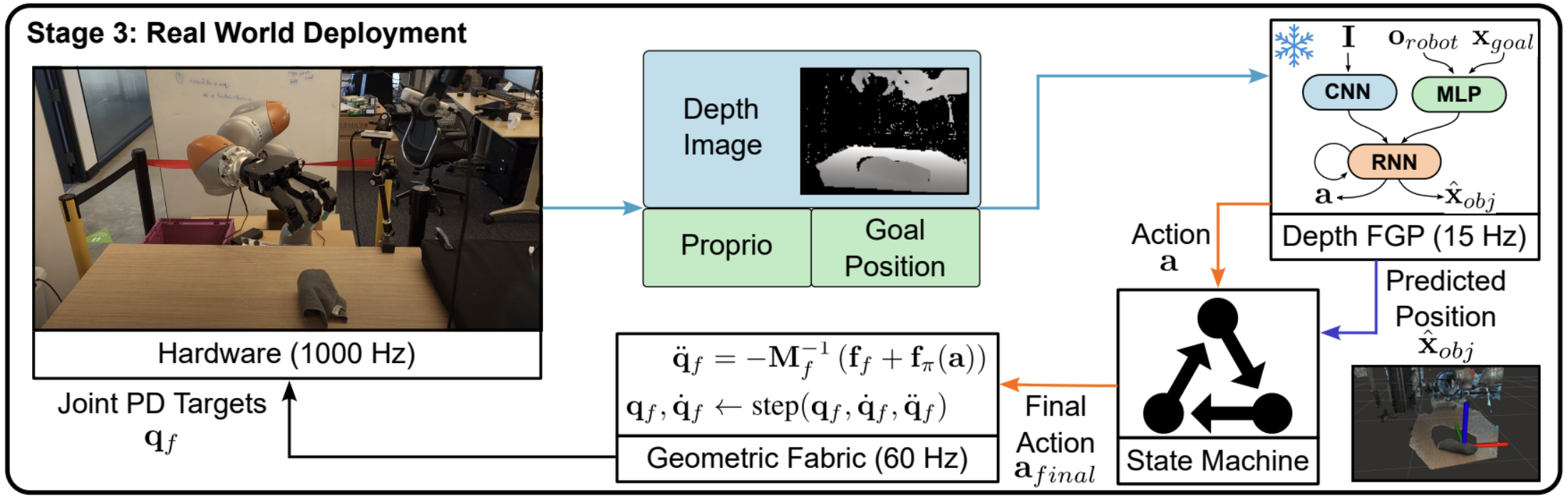
An example: High-Speed Obstacle Avoidance



Learning High-Speed Flight in the Wild, Loquercio et al., 2021

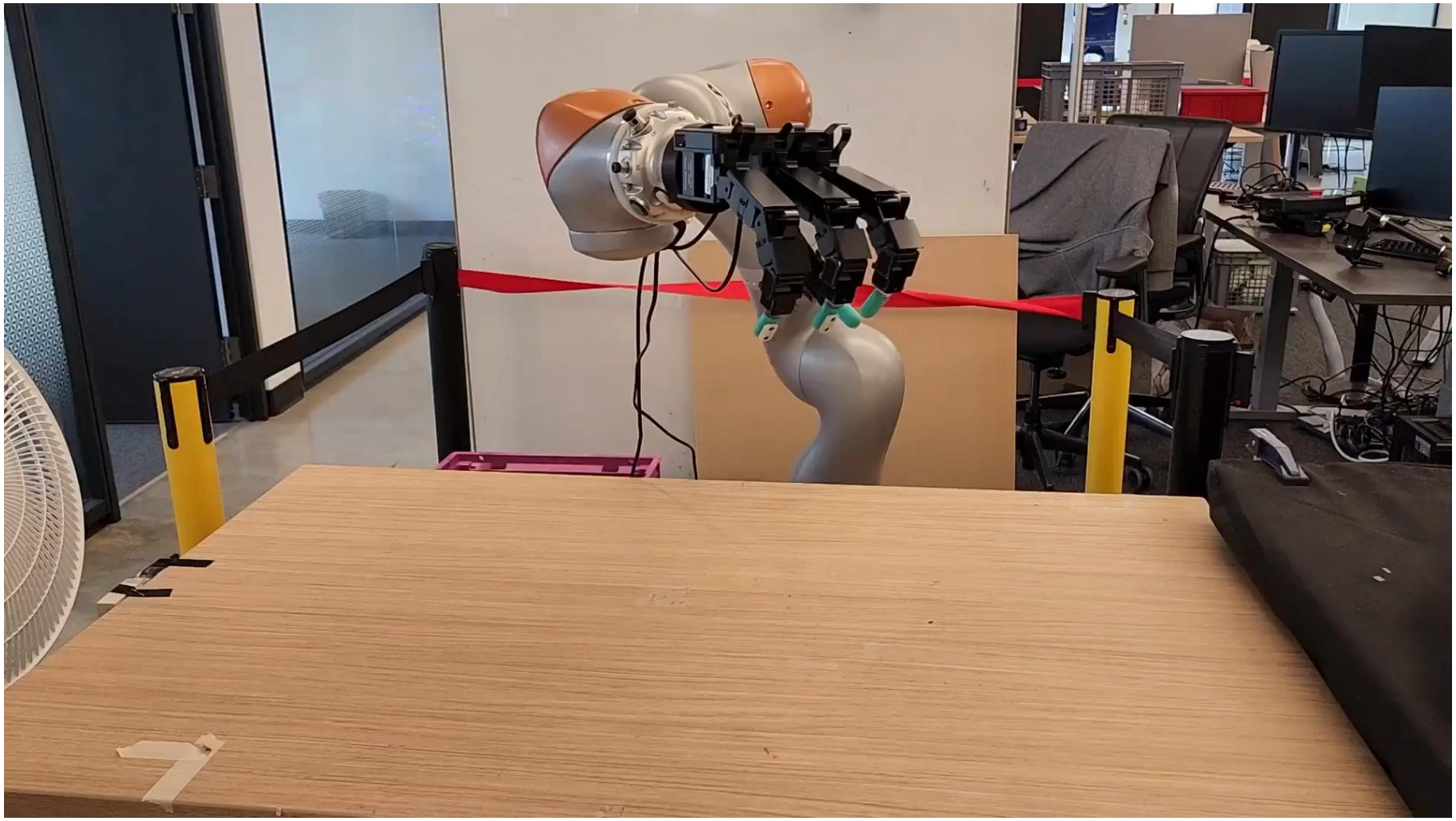
Loquercio et. al.,
Science Robotics, 2021

An example: Dexterous Manipulation



DextrAH-RGB: Visuomotor Policies to Grasp Anything with Dexterous Hands, Singh et al., 2025
DextrAH-G: Pixels-to-Action Dexterous Arm-Hand Grasping with Geometric Fabrics, Lum et al., 2024

An example: Dexterous Manipulation



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Abstraction-based Sim2Real

- **General idea:** train the policy on *curated* sensory/control abstractions that reduce the gap between simulation and real world.

- A neat way to introduce inductive bias in the policy learning process.

- Limitations?
  - Abstractions require modularity, which comes with several disadvantages (e.g., compounding errors, latency, computing the abstraction might be harder than the task itself).
  - Abstractions are mostly task-specific.

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Most papers use a mix of these techniques. But some applications require care.

Tips and Tricks to Make Your Sim2Real Pipeline Work

The Steps of a Sim2Real Pipeline

- Step 1: Decide on your abstractions!
  - **Sensory**
    - Which sensory inputs can I get in the real world?
    - What is the noise associated with these inputs?
    - Are these sensory inputs fast or slow to simulate? (Point clouds are very fast, but depth/RGB images are slow)
  - **Control**
    - At which level should my policy operate? (motor commands, joint positions, velocity commands, pose commands, etc.)
    - How well can you simulate the control hierarchy on which the policy will rely? (example: the Franka manipulator).

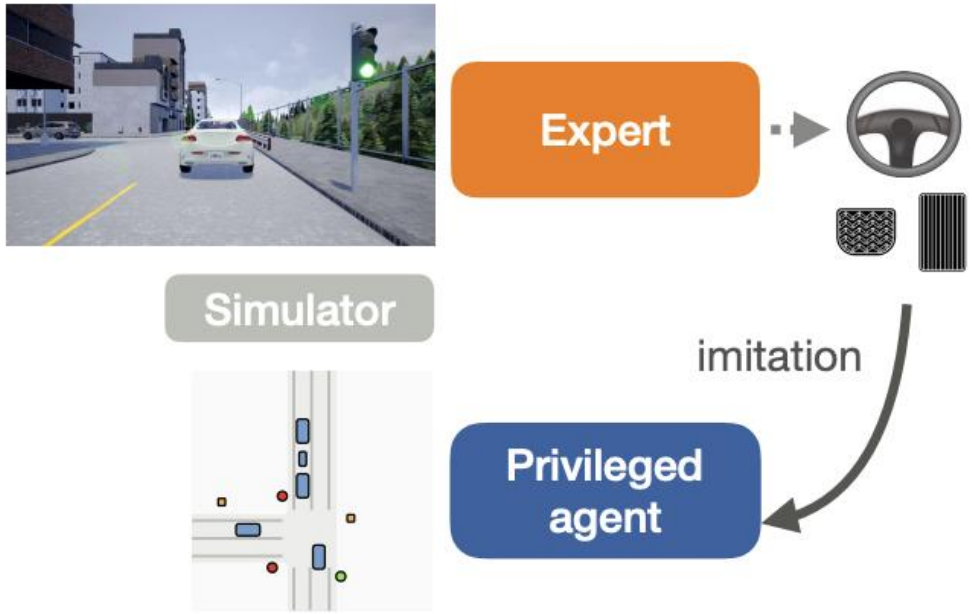
The Steps of a Sim2Real Pipeline

- Step 2: Decide on your strategy for policy training

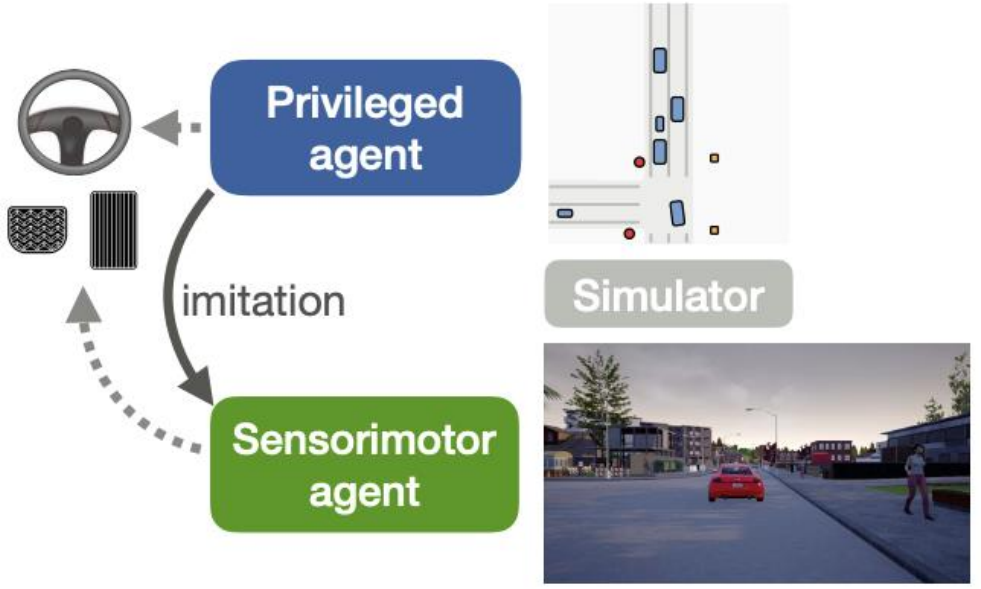
  - **Single Step?**
    - Mostly works if your policy is reactive and/or sensor simulation is fast.
    - Well-suited to policy learning via imitation.
    - More challenging for policy learning with RL: Might require very careful reward engineering.
    - Core advantage: the policy can be directly deployed on hardware.

  - **Two (or more) Steps? (Privileged Training + Distillation via Imitation)**
    - Train a privileged policy with ground-truth information (e.g., location of obstacles)
    - Distill the privileges policy into another policy with sensor observation (generally called the teacher-student paradigm)
    - Most common for policy learning with RL when you have some sensory inputs or control abstraction that are slow to simulate (e.g., images).

Two (or more) Steps for Policy Learning



(a) Privileged agent imitates the expert



(b) Sensorimotor agent imitates the privileged agent

Learning by cheating, Chen et al, 2019

The Steps of a Sim2Real Pipeline

- Step 3: Decide on your randomization/adaptation strategy

  - **Randomize and conquer**
    - Identify the parameters that are uncertain and might require randomization
    - Identify suitable randomization ranges
    - The less you randomize, the faster and more effective policy training will be.
    - The less you randomize, the lower the probability of effective sim2real.

  - **Shall I use an adaptation module (RMA-style)?**
    - If yes, you are forced to a two-step training procedure (see previous slide). However, it often helps performance.
    - If you're doing a two-step procedure anyway because your sensor simulation is slow, it is worth doing it.

The Steps of a Sim2Real Pipeline

- Step 4: Design your environment

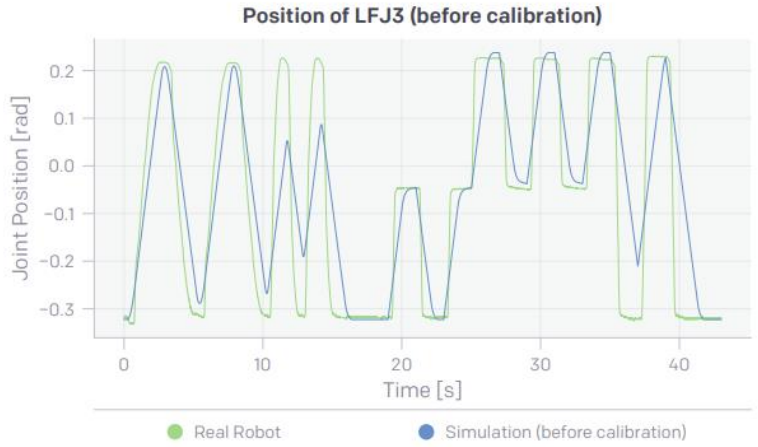
  - **One of the most complicated parts**
    - What objects do you need in the scene to accomplish the task?
    - Is geometry sufficient, or do you also need visual realism?
    - Scene randomization is important! The axes of randomization depend on your task.

  - **Do not overthink it**
    - Often, the environments in the simulation and the real world do not need to match exactly.
    - The more complex the scene, the slower the simulation will be.
    - Start simple and increase complexity if you notice specific failures.

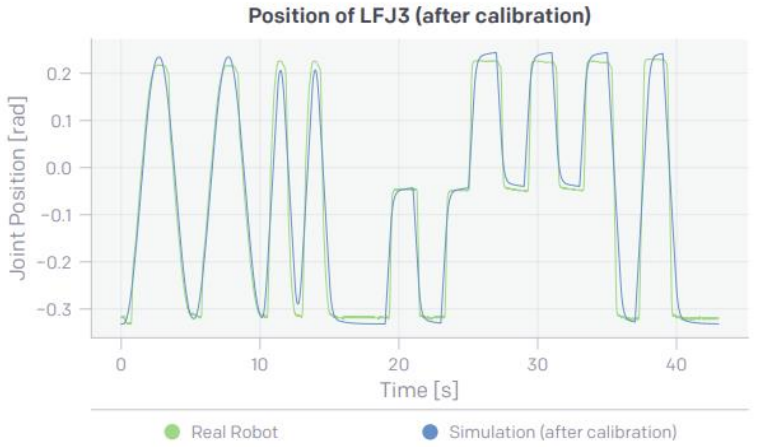
Tips to Improve Your Sim2Real Performance

Tune your control abstraction properly!

- Having the same PID gains in simulation and the real world is neither sufficient nor necessary.
- You need to match the behaviors as much as possible (the gains could potentially be different).
- Keep latency into account.



(a) Comparison against original simulation.



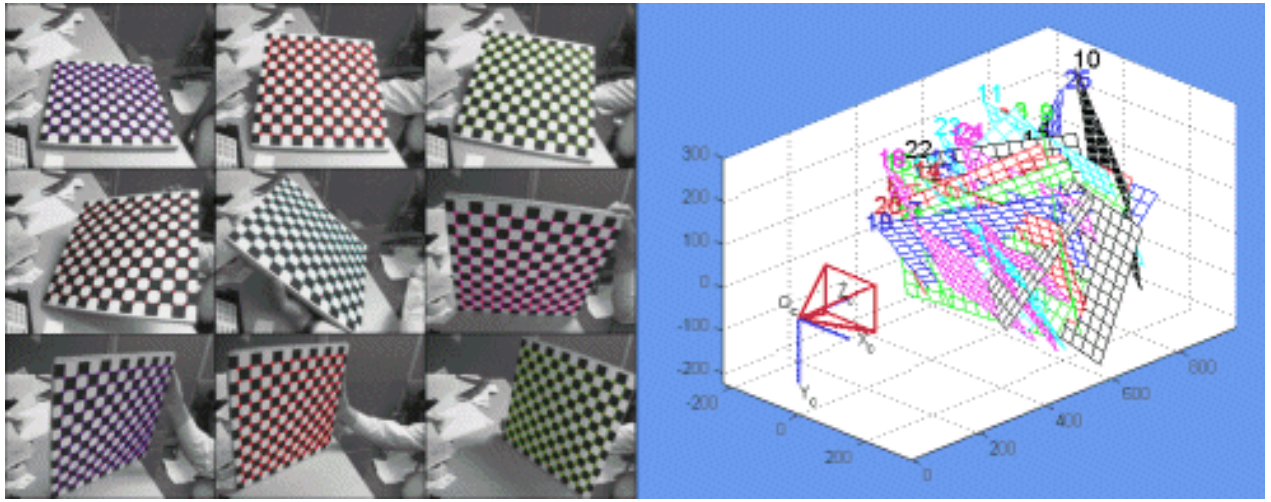
(b) Comparison against new simulation.

Solving Rubik's Cube with a Robot Hand, Akkaya et al.

Tips to Improve Your Sim2Real Performance

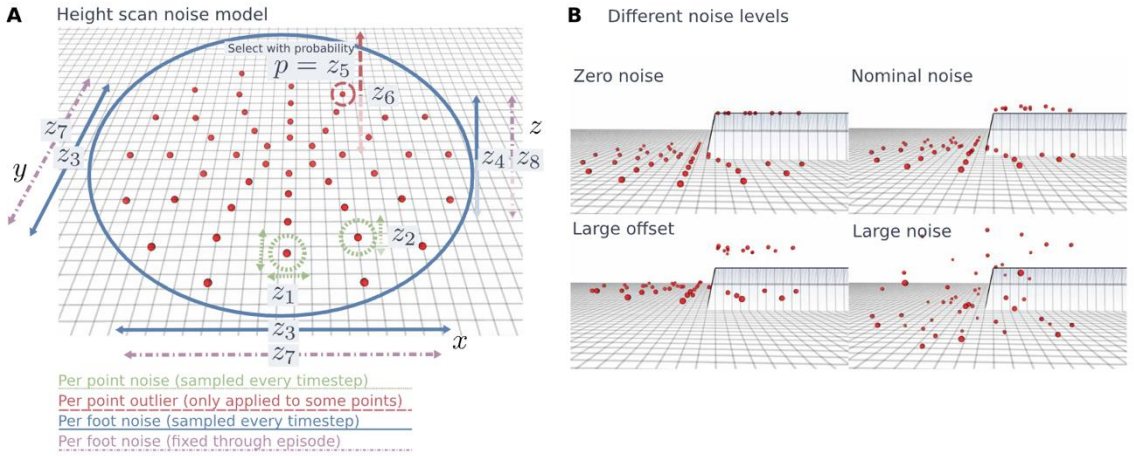
Calibrate your sensors

- Tiny errors in sensor placement can lead to vastly different observations.
- Do a good calibration (using off-the-shelf tools) and add a small randomization on top.



Tips to Improve Your Sim2Real Performance

- **Use noise models when matching the sensor-control abstractions is challenging.**



- **Train the noise models on real-world data**
  - Add a residual neural network to predict dynamics or sensor observations.
  - Examples:
    - $\mathrm{NM}^{dynamics}(\mathrm{s_t}, \mathrm{a_t}) = f_{real}(s_t, a_t) - f_{sim}(s_t, a_t)$
    - $\mathrm{NM}^{obs}(s_t) = obs_{real}(s_t) - obs_{sim}(s_t)$

Tips to Improve Your Sim2Real Performance

Evaluate often on the physical robot

- Unfortunately, often strong performance in simulation does not lead to strong performance in the real world.
  - **Corollary**: Checkpoint picking is hard; Different seeds of the same run could have vastly different performance.
  - **Sim2Sim** (e.g., Isaac to Mujoco) is often very informative in the early stage of a project.
- Do a detailed analysis of any real-world evaluation you do.
  - Did the control abstraction work as I expected?
  - Did the visual abstraction work as I expected?
  - How different is the behavior in the simulation and the real world?

High-Level Advice for Successful Sim2Real

- **Start simple, move slowly**
  - As end-to-end as possible, without complex sensor/control abstractions that are hard to match.
  - Increase the complexity of abstractions if real-world results are not as good.
  - Only add learning-based noise models if strictly necessary (they come with a lot of challenges in terms of training and generalization).
  - Don’t be afraid to mess around with the simulator’s engine (contact models, integrator, robot's physical parameters).
- **Use good engineering practices**
  - Don’t do more than one change at a time.
  - Don’t use ROS unless strictly necessary (modelling non-constant communication delays can be hard)
  - Use fast simulators, at least in early development.
  - (RL-Specific): Keep your rewards simple.

Discussion and Outlook

- Sim2Real is a promising approach for robot learning, because it enables:
  - Train safely
  - Carefully control the experience of the agent during training
  - Explore counterfactuals

- **Limitations:**
  - Not yet a clean science. It looks more like a collection of good practices
  - No good/scalable way to account for the semantic gap between simulated and real-world environments
    - **Corollary:** Environment design is often the hardest part of a sim2real project

- **Modern directions:**
  - Learning abstractions from data
  - Sim2Real from data-driven simulators
  - Continual learning of simulator, policy, and abstractions