RMA: Rapid Motor Adaptation for Legged Robots

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Presented by

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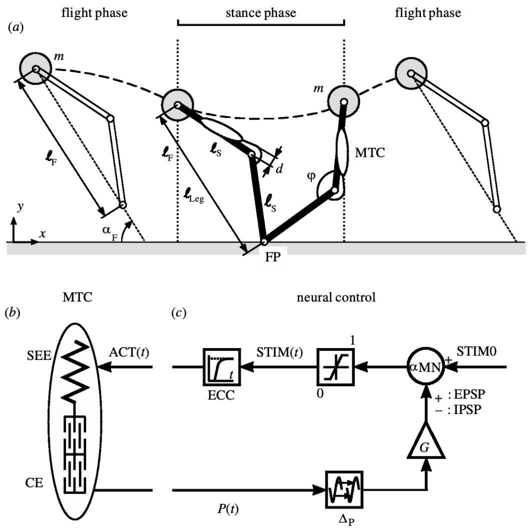
LEGGED ROBOTS

Legged robots are a type of mobile robot which use ***articulated limbs***, such as leg mechanisms, to provide locomotion.

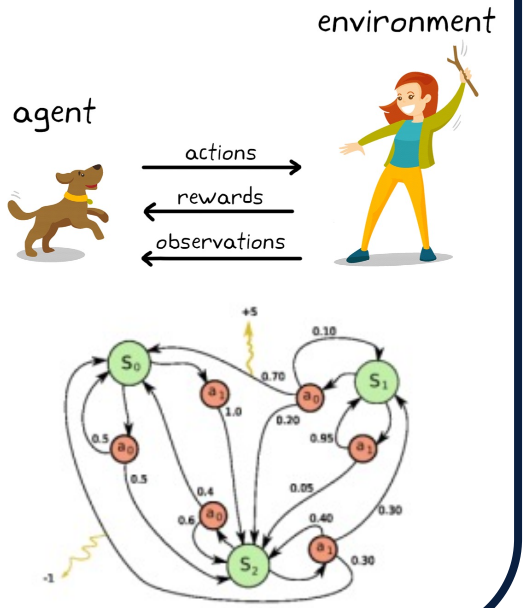
Quadruped robots

CONTROLLER

Traditional Methods

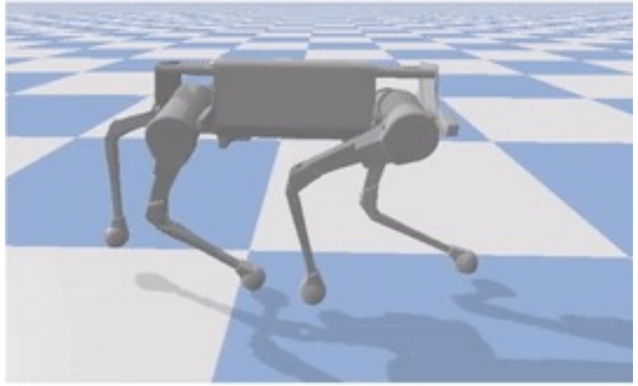


Learning-based Methods



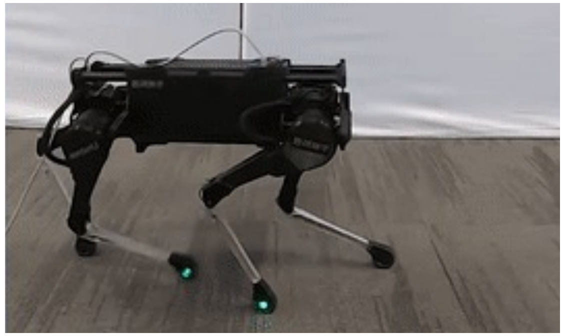
- Require considerable expertise on the part of the human designer

- Train in **simulation**, then transfer to the real-world using sim-to-real techniques



Generalization

Simulation → Reality



- The physical robot and its model in the simulator differ significantly
- Real-world terrains vary considerably
- The simulator fails to accurately capture the physics of the real world

For quadruped robots

To solve generalization problem, the authors proposed

Rapid Motor Adaptation

Learned entirely in ***simulation*** (why?) without using any domain knowledge

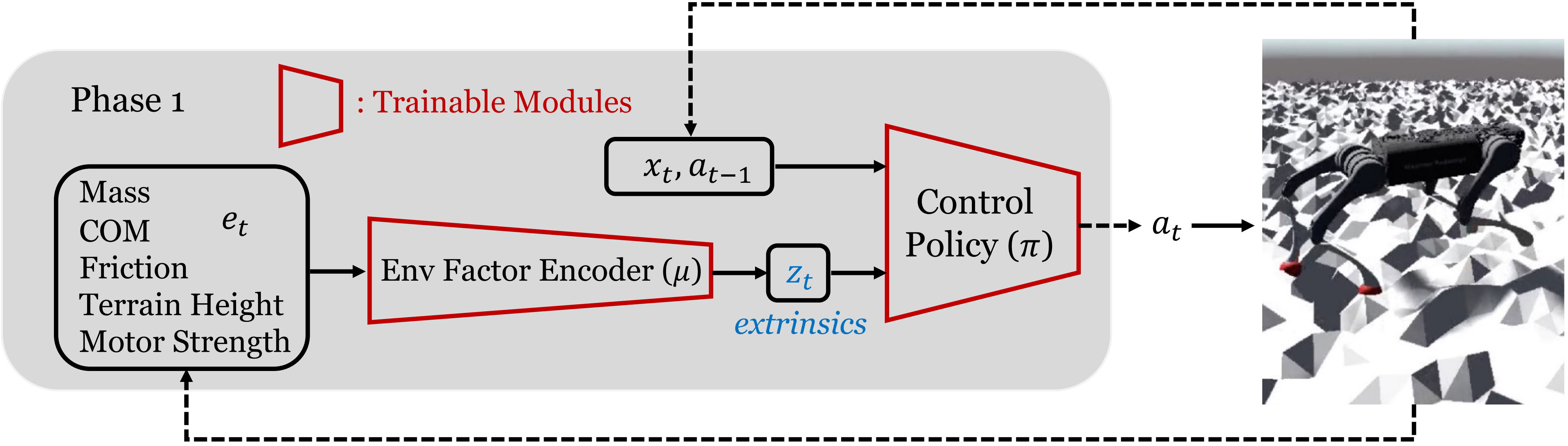
Deploy ***without*** fine-tuning

Rapid Motor Adaptation

Train in Simulation

Phase 1: Jointly train policy π and environmental factor encoder μ via Reinforcement Learning in simulation

$$a_t = \pi(x_t, a_{t-1}, z_t) = \pi(x_t, a_{t-1}, \mu(e_t))$$



Train in Simulation

Phase 1: Jointly train policy π and environmental factor encoder μ via Reinforcement Learning in simulation

$$J(\pi) = \mathbb{E}_{\tau \sim p(\tau|\pi)} \left[\sum_{t=0}^{T-1} \gamma^t r_t \right]$$

where $\tau = \{(x_0, a_o, r_0), (x_1, a_1, r_1), \dots\}$ is the trajectory of the agent when executing policy π, γ is the hyperparameter, which is set to 0.998 according to the supplementary.

(More in discussion)
Follow a designed *curriculum*
The reward function r_t is the *weighted* sum of

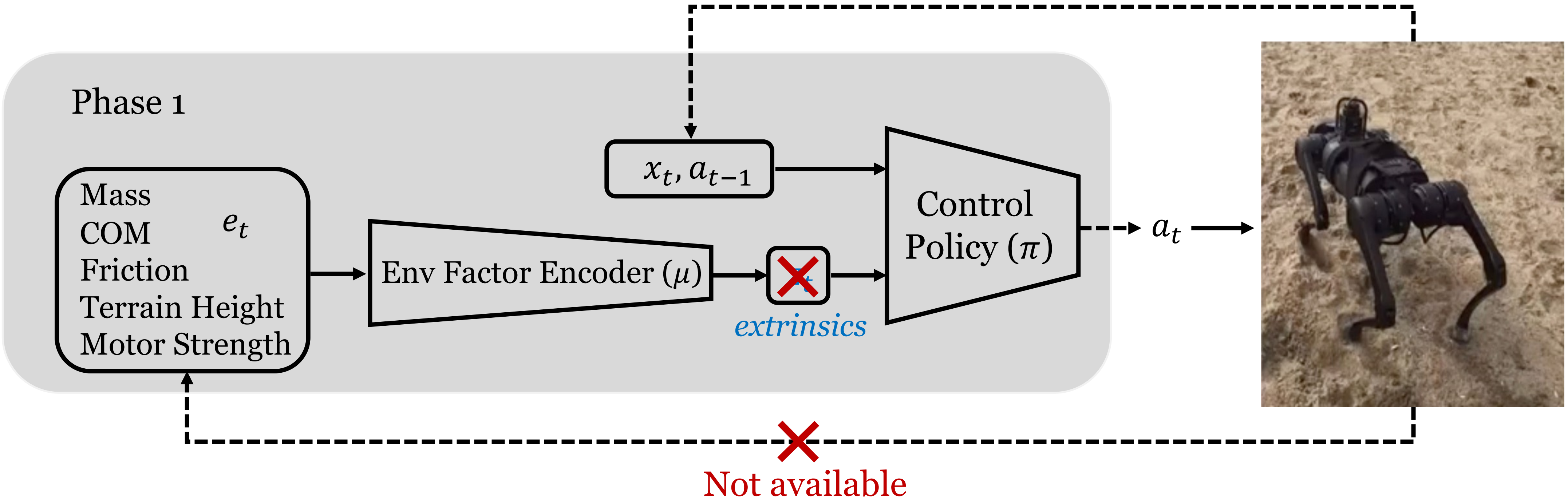
1) Forward: $\min(v_x^t, 0.35)$
2) Lateral Movement and Rotation: $-\|v_y^t\|^2 - \|\omega_{\mathtt{yaw}}^t\|^2$
3) Work: $-|\boldsymbol{\tau}^T \cdot (\mathbf{q}^t - \mathbf{q}^{t-1})|$
4) Ground Impact: $-\|\mathbf{f}^t - \mathbf{f}^{t-1}\|^2$
5) Smoothness: $-\|\boldsymbol{\tau}^t - \boldsymbol{\tau}^{t-1}\|^2$
6) Action Magnitude: $-\|\mathbf{a}^t\|^2$
7) Joint Speed: $-\|\dot{\mathbf{q}}^t\|^2$
8) Orientation: $-\|\boldsymbol{\theta}_{\mathtt{roll,\ pitch}}^t\|^2$
9) Z Acceleration: $-\|v_z^t\|^2$
10) Foot Slip: $-\|\mathrm{diag}(\mathbf{g}^t) \cdot \mathbf{v_f}^t\|^2$

Penalize for jerky and inefficient motions

Bioenergetics-inspired, learn walking policies ***without*** using any reference demonstrations by minimizing work and ground impact.

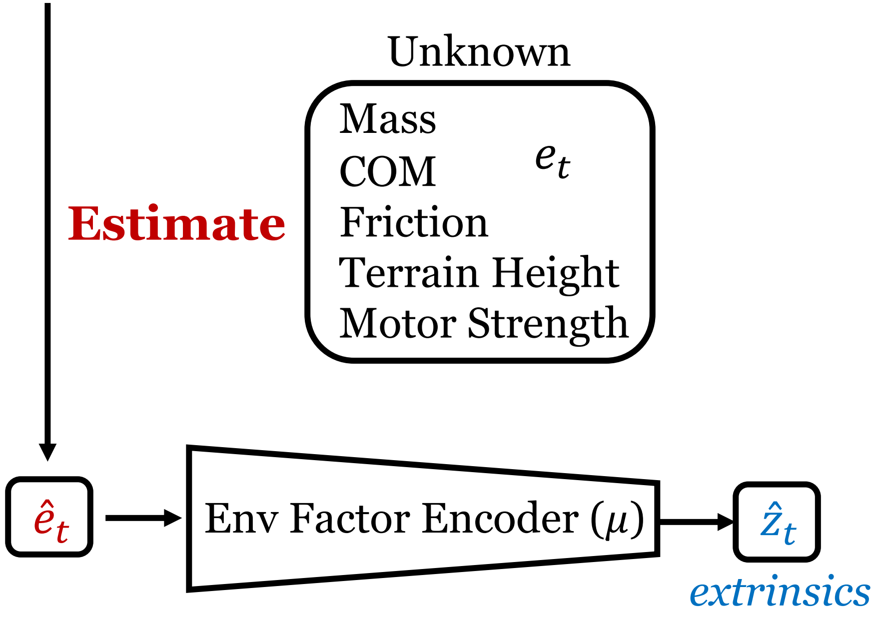
How to Deploy

However, environmental factors are ***not*** available when deploying.



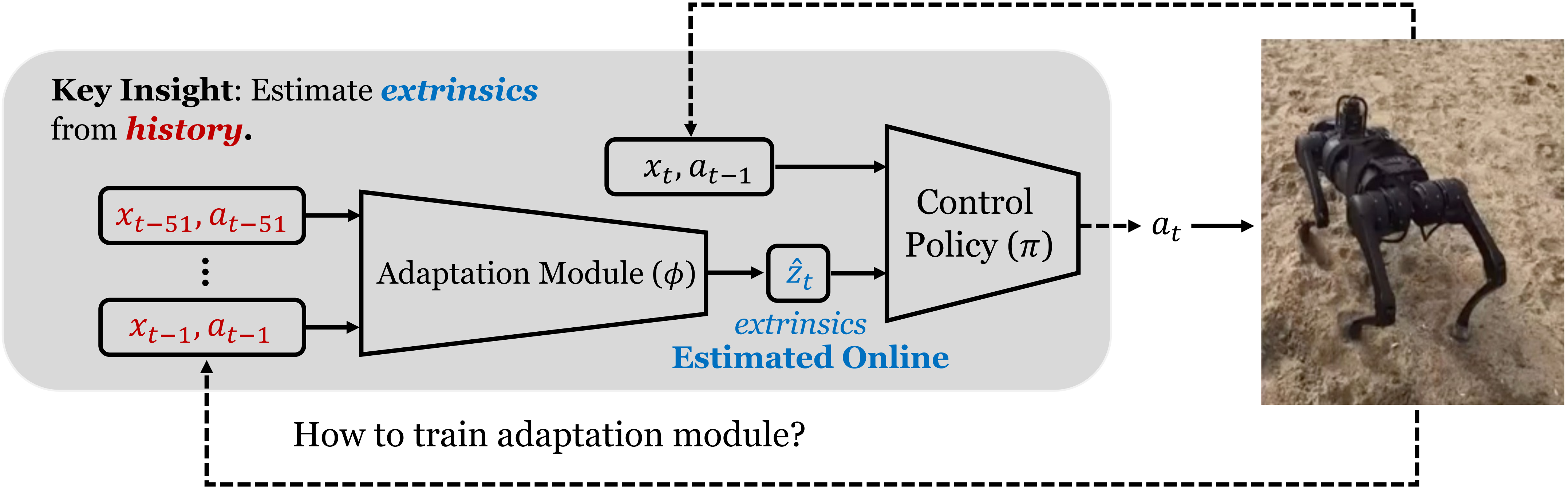
How to Deploy

The task of **System Identification** **is Very Hard!!**



Adaptation Module

Instead of system identification, **directly estimate the *extrinsics*.**

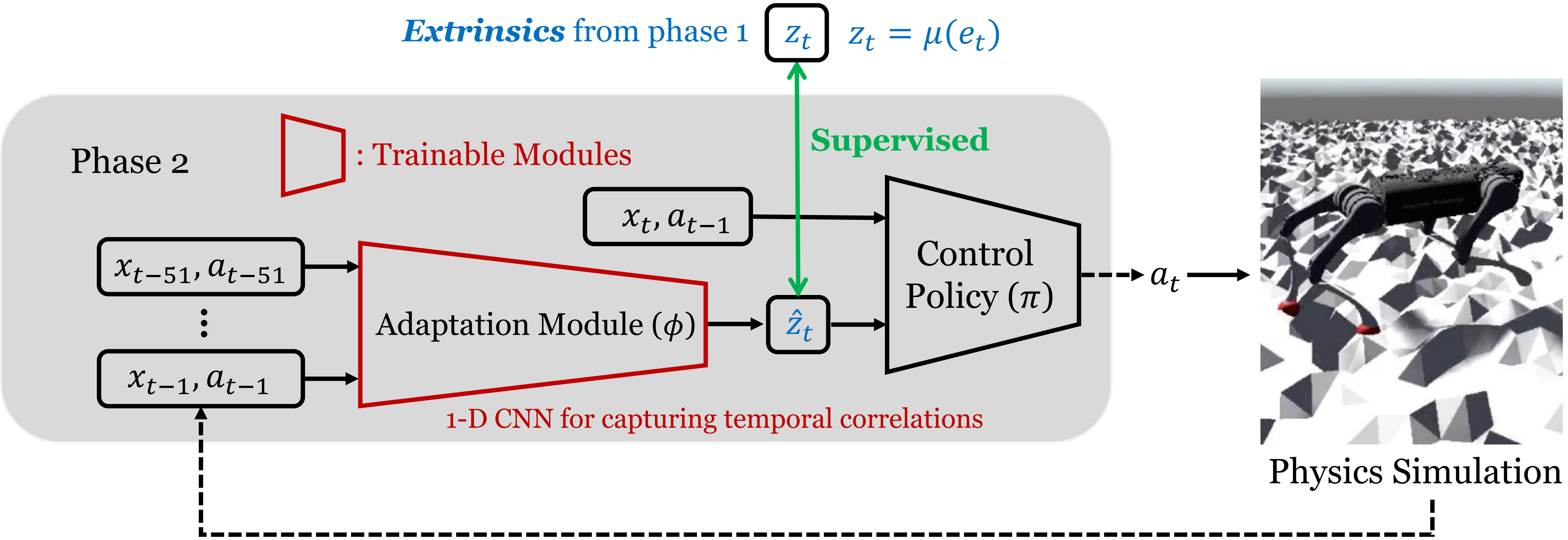


How to train adaptation module?

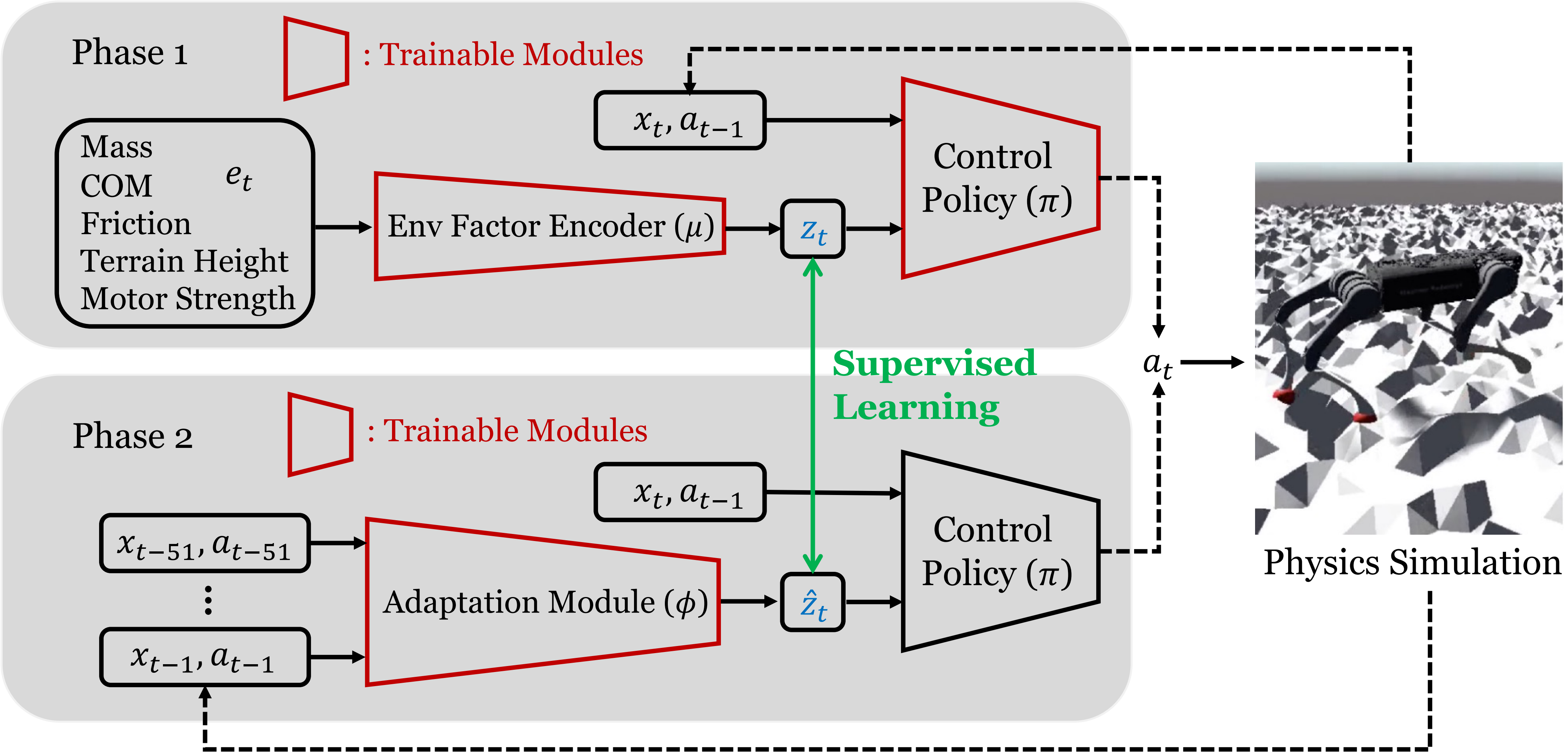
Training Adaptation Module

Phase 2: Train adaptation module ϕ via Supervised Learning in simulation, $k = 50$ (0.5s) in experiments

$$\hat{z}_t = \phi(x_{t-k:t-1}, a_{t-k:t-1})$$



Training Scheme



Training Algorithm

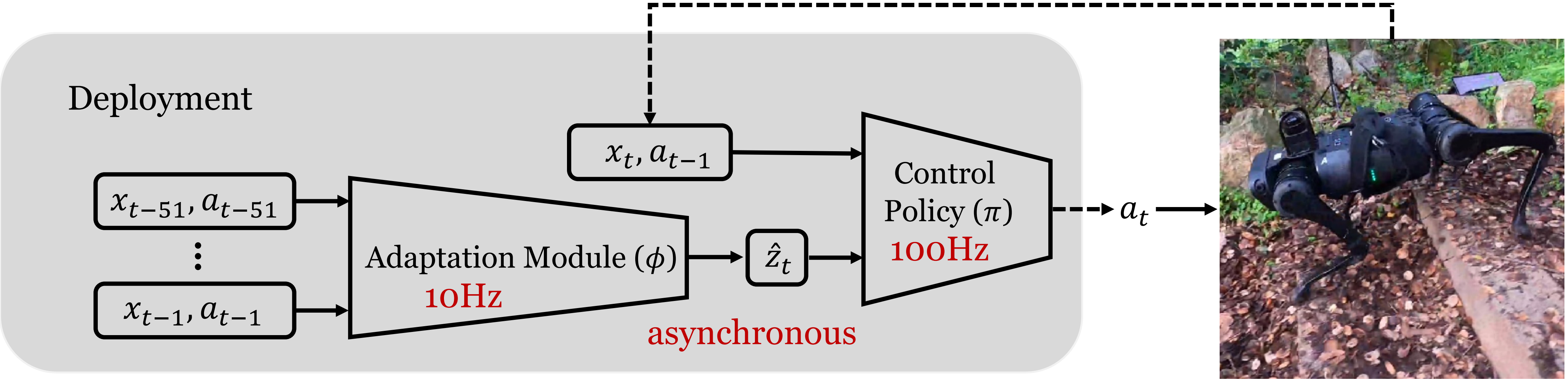
Phase 1 Randomly initialize the base policy π;
Randomly initialize the environmental factor encoder
μ; Empty replay buffer D_1;
for $0 \leq \text{itr} \leq N^1_{\text{itr}}$ **do**
  for $0 \leq i \leq N_{\text{env}}$ **do**
    $x_0, e_0 \leftarrow$ envs[i].reset();
    for $0 \leq t \leq T$ **do**
      $z_t \leftarrow \mu(e_t)$;
      $a_t \leftarrow \pi(x_t, a_{t-1}, z_t)$;
      $x_{t+1}, e_{t+1}, r_t \leftarrow$ envs[i].step(a_t);
      Store $((x_t, e_t), a_t, r_t, (x_{t+1}, e_{t+1}))$ in D_1;
    end
  end
  Update π and μ using PPO [48];
  Empty D_1;
end

Phase 2 Randomly initialize the adaptation module ϕ
parameterized by θ_ϕ; Empty mini-batch D_2;
for $0 \leq \text{itr} \leq N^2_{\text{itr}}$ **do**
  for $0 \leq i \leq N_{\text{env}}$ **do**
    $x_0, e_0 \leftarrow$ envs[i].reset();
    for $0 \leq t \leq T$ **do**
      $\hat{\mathbf{z}}_\mathbf{t} \leftarrow \phi(x_{t-k:k}, a_{t-k-1:k-1})$;
      $z_t \leftarrow \mu(e_t)$;
      $a_t \leftarrow \pi(x_t, a_{t-1}, \hat{\mathbf{z}}_\mathbf{t})$;
      $x_{t+1}, e_{t+1}, \_ \leftarrow$ envs[i].step(a_t);
      Store $(\hat{z}_t, z_t)$ in D_2;
    end
  end
  $\theta_\phi \leftarrow \theta_\phi - \lambda_{\theta_\phi} \nabla_{\theta_\phi} \frac{1}{T N_{\text{env}}} \sum \|\hat{z}_t - z_t\|^2$;
  Empty D_2;
end

Deploy in Real-World

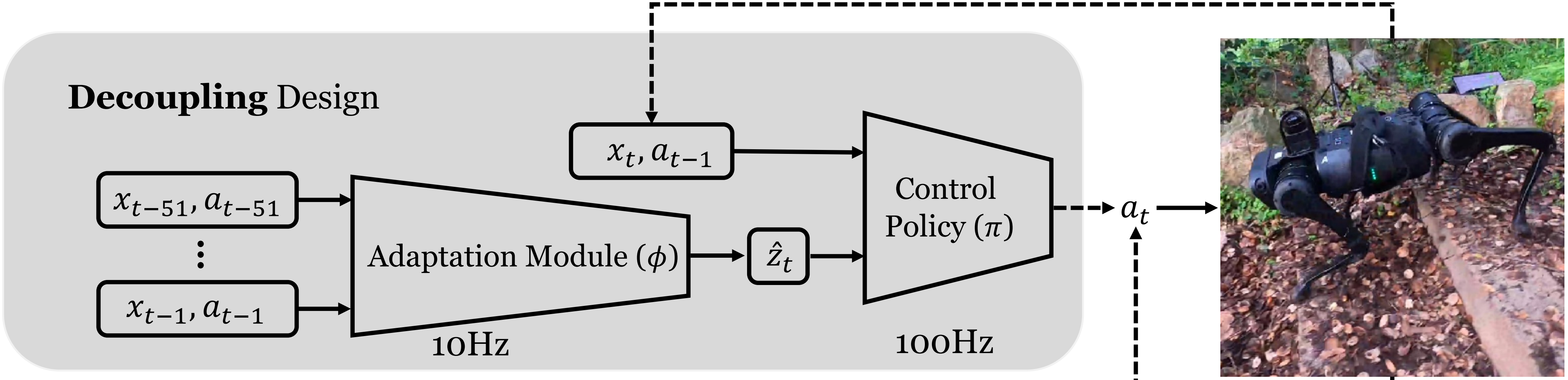
Deployment: The adaption module and the control policy run ***asynchronously***.

control policy uses most recent $\hat{z}_t$



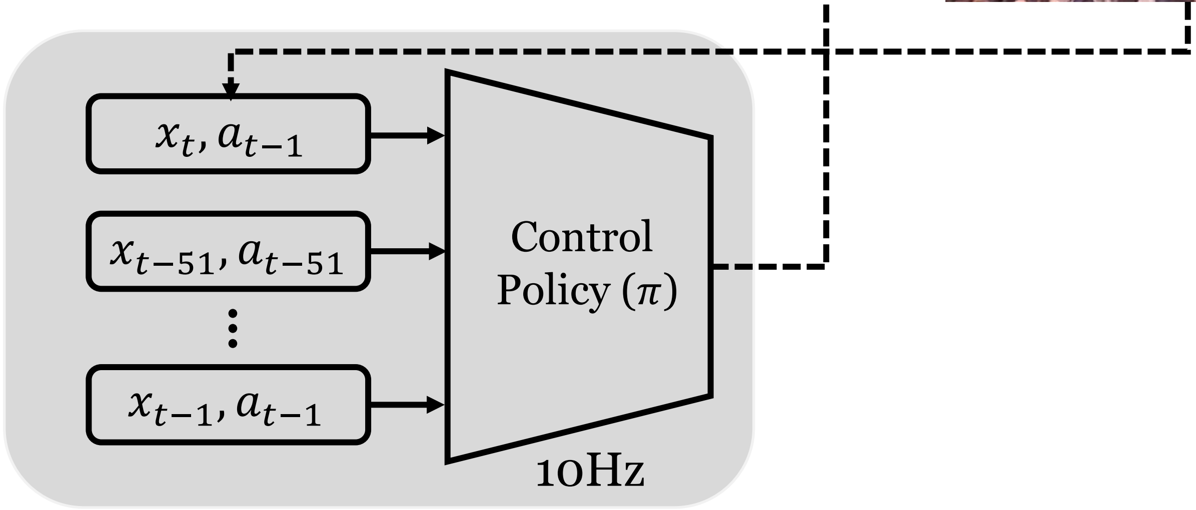
Intuition: $\hat{z}_t$ changes relatively infrequently in the real-world.

Necessity of Adaptation Module



Why decoupling?

- **Unnatural** gaits and **poor** performance in simulation.
- Can only run at **10Hz** on the on-board processor.
- Asynchronous design is critical for a **seamless** deployment, without needing calibration.



Environmental Variation

Parameters	Training Range	Testing Range
Friction	[0.05, 4.5]	[0.04, 6.0]
K_p	[50, 60]	[45, 65]
K_d	[0.4, 0.8]	[0.3, 0.9]
Payload (Kg)	[0, 6]	[0, 7]
Center of Mass (cm)	[-0.15, 0.15]	[-0.18, 0.18]
Motor Strength	[0.90, 1.10]	[0.88, 1.22]
Re-sample Probability	0.004	0.01

TABLE I: Ranges of the environmental parameters.

Experiment

Baselines

- **A1 Controller**: Default controller
- Robustness through Domain Randomization (**Robust**): The base policy is trained without z_t to be robust to the variations in the training range
- Expert Adaptation Policy (**Expert**): In simulation, we can use the true value of the extrinsics vector z_t. This is an upper bound to the performance of RMA.
- **RMA w/o Adaptation**: Run adaptation module for the first timestamp and then *freeze* it.
- **System Identification**: Directly predict the environmental factor e^t.
- Advantage Weighted Regression for Domain Adaptation (**AWR**): Optimize z^t offline using AWR by using real-world rollouts of the policy in the testing environment.

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Robotics: Science and Systems 2021

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Gait pattern

Torque of knee

Components of extrinsics

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EXPERIMENT

Results in simulation

	Success (%)	TTF	Reward	Distance (m)	Samples	Torque	Smoothness	Ground Impact
Robust [52, 40]	62.4	0.80	4.62	1.13	0	527.59	122.50	4.20
SysID [57]	56.5	0.74	4.82	1.17	0	565.85	149.75	4.03
AWR [41]	41.7	0.65	4.17	0.95	40k	599.71	162.60	4.02
RMA w/o Adapt	52.1	0.75	4.72	1.15	0	524.18	106.25	4.55
RMA	73.5	0.85	5.22	1.34	0	500.00	92.85	4.27
Expert	76.2	0.86	5.23	1.35	0	485.07	85.56	3.90

TABLE II: **Simulation Testing Results:** We compare the performance of our method to baseline methods in simulation. Our train and test settings are listed in Table I. We resample the environment parameters within an episode with a re-sampling probability of 0.01 per step during testing. Baselines and metrics are defined in Section V. The numbers reported are averaged over 3 randomly initialized policies and 1000 episodes per random initialization. RMA beats the performance of all the baselines, with only a slight degradation in performance compared to the Expert.

Discussion

The reward function r_t is the *weighted* sum of

[20, 21, 0.002, 0.02, 0.001, 0.07, 0.002, 1.5, 2.0, 0.8]

1) Forward: $\min(v_x^t, 0.35)$
2) Lateral Movement and Rotation: $-\|v_y^t\|^2 - \|\omega_{\texttt{yaw}}^t\|^2$
3) Work: $-|\boldsymbol{\tau}^T \cdot (\mathbf{q}^t - \mathbf{q}^{t-1})|$
4) Ground Impact: $-\|\mathbf{f}^t - \mathbf{f}^{t-1}\|^2$
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If naively train the agent with the above reward function, it learns to **stay in place** because of the penalty terms on the movement of the joints.

To prevent this collapse, the training starts with very small penalty coefficients, and then **gradually** increase the strength of these coefficients using a fixed curriculum.

DISCUSSION

@83_f3
For the training curriculum, …

I believe this is an effective method to maintain the reward function without having the collapse. However, I wonder if there are better ways to define the reward function or training curriculum, so that the agent is more "motivated" to move.

@ One Reply of 83_f3
In [1], instead of varying the rewards, the researchers varied the simulation itself to accommodate the robot's current skill level. But from what I remember, this involved hand-designing a measure of "difficulty", which likely took a lot of effort compared to implementing a scaling reward function.

@83_f5
One thought on this work: the reward function seems **highly hand-crafted**. I wonder if the authors tried simpler reward functions and did not see good performance?

In general, it seems like there is no good way to provide general enough rewards (from a human perspective) for these types of task-specific RL problems. I wonder if over time we will develop models that can for example take natural language instructions and learn behaviors that satisfy said instructions. Curiosity-based learning seems to work to some extent, but without any specific reward you might end up with a robot that's really good at doing backflips instead of one that can walk.

[1] Lee J, Hwangbo J, Wellhausen L, et al. Learning quadrupedal locomotion over challenging terrain[J]. Science robotics, 2020, 5(47): eabc5986.

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Thanks!