Supplementary Material for X-Nav: Learning End-to-End Cross-Embodiment Navigation for Mobile Robots

A. Reward Function for Expert Policies

The reward function is computed as $r = r_{task} * \exp(c_{reg} * r_{reg})$ [1]. The definition of the task reward r_{task} and regularization rewards r_{reg}^{wheel} and r_{reg}^{quad} are defined below in Table A.I.

TABLE A.I: REWARD FUNCTION

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Reward	Expression	Explanation					
r_{task}	$r_{pos,(soft/hard)} = \frac{c_{1,(soft/hard)}}{1 + \left\ \frac{d_{goal}}{c_{2,(soft/hard)}} \right\ ^2} \cdot \mathbb{1}(t > T - T_r)$	Encourages the robot to move to the goal position [2]. T_r denotes the duration of timesteps for which r_{pos} is activated. $r_{pos,soft}$ is a dense reward used to encourage exploration using a larger c_2 , $c_{2,soft}$, while $r_{pos,hard}$ is a sparse reward for accurate position tracking using a smaller c_2 , $c_{2,hard}$.					
	$r_{fwd} = c_{fwd} \cdot \exp\left(-\frac{\ v_{ref} - v_x\ ^2}{\sigma_{vel}}\right) \cdot \mathbb{1}(\delta_{goal} < \sigma_{direct})$	Encourages the robot to move forward at the reference speed v_{ref} . δ_{goal} is the heading error relative to the goal, and σ_{direct} is an angle threshold for the robot heading in the correct direction.					
r_{reg}^{wheel}	$r_{reg}^{wheel} = c_a \dot{a} ^2$ $r_{collide} = c_{collide} \cdot \mathbb{1}_{collide}$	\dot{a} denotes the action rate. $\mathbb{1}_{collide}$ indicates whether a collision has happened between the robot and obstacles.					
	$r_{stop} = \frac{c_{1,stop}}{1 + \left\ \frac{a}{c_{2,stop}} \right\ ^2} \cdot \mathbb{1}(\delta_{goal} < \sigma_{direct})$	Ensures the robot stops at its goal position. σ_{hard} is a distance threshold used to determine when the robot has reached its goal position.					
r_{reg}^{quad}	$r_{stop} = \frac{c_{1,stop}}{1 + \left\ \frac{q - q_{nom}}{c_{2,stop}} \right\ ^2} \cdot \mathbb{1}(d_{goal} < \sigma_{hard})$	Ensures the robot stops at its goal position. q_{nom} are the nominal joint positions, defined as the initial joint angles of the robot when it stands in its default posture.					
	$r_{collide} = c_{collide} \cdot \mathbb{1}_{collide} \qquad r_{\ddot{q}} = c_{\ddot{q}} \ \ddot{q}\ ^2$	\ddot{q} is the joint acceleration.					
	$r_{v_z} = c_{v_z} v_z^2 \qquad \qquad r_{\omega} = c_{\omega} (\omega_{xy}^2)$	v_z is the vertical velocity of the robot base, and ω_{xy} is the angular velocity of the base around x and y axes.					
	$r_{\tau} = c_{\tau} \tau ^2$ $r_{\dot{a}} = c_{\dot{a}} a_t - a_{t-1} ^2$	au is the joint torque.					
	$ \begin{aligned} r_{\tau} &= c_{\tau} \ \tau\ ^2 \\ r_{\underline{dev}} &= c_{\underline{dev}} \cdot \ q - q_{nom}\ ^2 \end{aligned} \qquad \begin{aligned} r_{\underline{a}} &= c_{\underline{a}} \ a_t - a_{t-1} ^2 \\ r_{\underline{a}} &= c_{\underline{a}} \ a_t - 2a_{t-1} + a_{t-2} ^2 \end{aligned} $	Penalizes joint deviation from the nominal joint positions.					
	$r_{swing} = c_{swing} \cdot \sum_{i=1}^{4} (1 - s_i) \cdot (1 - \exp(-f_i^2 / \sigma_{force}))$	Encourages the quadruped feet to track the leg swing phase [1]. f_i is the contact force of the i-th foot of the quadruped. s_i is the desired contact state of the foot.					
	$r_{stance} = c_{stance} \cdot \sum_{i=1}^{i=1} s_i \cdot (1 - \exp\left(-\ \mathbf{v}_{foot,i}\ ^2 / \sigma_{foot}\right))$	Encourages the quadruped feet to track the leg stance phase [1]. $\mathbf{v}_{foot,i}$ is the velocity of the i-th foot.					
	$r_{slide} = c_{slide} \cdot \sum_{i=1}^{4} \ \mathbf{v}_{foot,i}^{xy}\ \cdot \mathbb{1}(f_i > f_{thresh})$	Avoids feet sliding on the ground. f_{thresh} is a force threshold for determining feet contact.					

^{*} $c_{1,(soft/hard)}$, $c_{2,(soft/hard)}$, c_{fwd} , $c_{1,stop}$, $c_{2,stop}$, $c_{collide}$, $c_{\dot{\alpha}}$, c_{v_z} , c_{ω} , c_{τ} , $c_{\ddot{q}}$, c_{av} , $c_{\ddot{\alpha}}$, c_{swing} , c_{stance} , c_{slide} and c_{reg} are all constants.

B. Parameters and Value Ranges for Embodiment Randomization

TABLE B.I: PARAMETERS FOR EMBODIMENT RANDOMIZATION

Type	Parameters	Range	Parameters	Range
	Base length	[0.24, 0.91] m	Thigh mass	[0.56, 1.69] kg
	Base width	[0.16, 0.39] m	Calf radius	[0.02, 0.05] m
Small-Sized	Base height	[0.06, 0.21] m	Calf length	[0.12, 0.39] m
Quadrupeds	Base mass	[4.8, 19.5] kg	Calf mass	[0.12, 0.39] kg
	Thigh radius	[0.02, 0.05] m	Motor P gain	[0.7, 1.3]
	Thigh length	[0.16, 0.46] m	Motor D gain	[0.7, 1.3]
	Base length	[0.56, 1.04] m	Thigh mass	[2, 5.2] kg
	Base width	[0.28, 0.52] m	Calf radius	[0.02, 0.04] m
Large-Sized	Base height	[0.14, 0.26] m	Calf length	[0.24, 0.36] m
Quadrupeds	Base mass	[24, 39] kg	Calf mass	[0.4, 0.6] kg
	Thigh radius	[0.03, 0.05] m	Motor P gain	[0.5, 1.3]
	Thigh length	[0.24, 0.39] m	Motor D gain	[0.5, 1.3]
Wheeled	Base length	[0.3, 0.8] m	Base height	[0.15, 0.3] m
Robots	Base width	[0.2, 0.65] m	Base mass	[5, 20] kg

C. Parameters and Value Ranges for Domain Randomization

TABLE C.I: PARAMETERS AND VALUE RANGES FOR DOMAIN RANDOMIZATION

Parameters	Ranges	Parameters	Ranges
Static friction	[0.7, 1.1]	Push disturbance	[-0.5, 0.5] m/s
Dynamic friction	[0.6, 1.0]	Push Interval	[4, 8] s
Added mass	[0.0, 2.0] kg	Ray distance noise	[-0.1, 0.1] m
Linear velocity noise	[-0.1,0.1] m/s	Angular velocity noise	[-0.1, 0.1] rad/s
Projected gravity noise	$[-0.05, 0.05] \text{ m/s}^2$	Joint velocity noise	[-1.0, 1.0] rad/s
Joint position noise	[-0.01, 0.01] rad	Motor Delay	[0.02, 0.08] s

D. Hyperparameters and Values

TABLE D.I: HYPERPARAMETERS AND VALUES

Parameter	Value	Parameter	Value	Parameter	Value
x_{scan}	2.5 m	y_{scan}	2.5 m	$c_{collide}$	-40
$c_{1,soft}$	10	$c_{2,soft}$	5	T_r	3 s
$c_{1,hard}$	15	$c_{2,hard}$	0.5	c _{dev}	-1
v_{ref}	[0.5,1.0] m/s	c_{ω}	-0.05	T	12 s
σ_{direct}	1.75 rad	$c_{ au}$	-0.0002	c_{v_z}	-2
σ_{hard}	0.5 m	$c_{\dot{a}}$	-0.01	σ_{close}	0.5 m
$c_{1,stop}$	10	$c_{\ddot{q}}$	-2.5e-7	σ_{far}	3.0 m
$C_{2,stop}$	0.2	c _ä	-0.05	c_{fwd}	2
c_{swing}	-5	c_{stance}	-5	C _{slide}	-5

References

- [1] G. B. Margolis and P. Agrawal, "Walk These Ways: Tuning Robot Control for Generalization with Multiplicity of Behavior," in *Proc. Conf. Robot Learn.*, 2022, pp. 1-14.
- [2] J. Jin *et al.*, "Resilient Legged Local Navigation: Learning to Traverse with Compromised Perception End-to-End," 2023, *arXiv*:2310.03581.