

Local Planning under Asymmetric Collision Geometries Across Embodiments

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PUBLISHED

September 22, 2026

REGISTERED

September 25, 2026

RECORD TYPE

Preprint

ABSTRACT

Local planners that run across quadrupeds, wheeled robots, and humanoids commonly represent every body by a symmetrically inflated disk or a static footprint, discarding the swing envelope of the legs, humanoid headroom, and the directional structure of clearance. This paper builds an embodiment-accurate collision layer on the AgniNav configuration-driven backbone. The layer replaces the static envelope with a configuration-dependent collision set, formed by the footprint and a phase-indexed leg-swing volume for quadrupeds, a body envelope for wheeled rovers, and a full-body capsule with arm reach and a headroom term for humanoids, and it scores candidate trajectories with a clearance cost that is anisotropic in each body frame. The planner is evaluated in 15 Isaac Lab mixed-embodiment scenes with diagonal gaps of 45 to 75 degrees, cluttered corridors, and multi-robot proximity, across four embodiments, five seeds, and 30 episodes each. Relative to symmetric inflation, the method raises the feasible passage width gain from 14.2 to 14.8 percent, lowers the collision rate from 0.19 to 0.18 per km, and lowers the 95th-percentile planner runtime from 6.9 to 6.4 ms, while the aggregate spurious-stoppage rate is unchanged at 0.3 per episode. The aggregate gains are modest and concentrate in specific situations: in a 60 degree, 71 cm diagonal gap where the symmetric-inflation quadruped fails 12 of 30 attempts, the swing-aware quadruped passes at 1.2 m/s with 8 cm clearance, and in one corridor the full-body humanoid model reduces spurious stoppages near a wheeled robot from 3.1 to 0.4 per episode.

INDEX TERMS local planning, collision geometry, cross-embodiment navigation, legged robots, humanoid robots, anisotropic clearance

KAGG NOTE Embodiment-accurate collision geometry yields small aggregate gains but clear gains in specific geometric bottlenecks, and a uniform margin is worse than no swing model at all.

01 Introduction

Cross-embodiment local planning aims to let a single navigation stack drive robots whose bodies differ substantially. Configuration-driven planners such as AgniNav [1] and CeRLP [2] make this practical by separating an environment-centric geometric representation from an explicit robot configuration that declares body geometry, sensing, and velocity limits. Once the configuration is explicit, the remaining question is how faithfully it describes the volume that the robot actually occupies while it moves.

In most deployed stacks the answer is coarse. A quadruped, a six-wheeled rover, and a humanoid are each reduced to a disk whose radius is the circumscribed radius of the body plus a safety margin, or at best to a static rectangle. These approximations differ from the true occupied volume in ways that depend on the embodiment. A walking quadruped sweeps its lower legs outside the trunk footprint in a pattern that depends on gait phase and speed, mostly in the fore-aft direction. A rover has a rigid envelope with no swing component but substantial length. A humanoid is narrow at foot level, wide at shoulder level when the arms swing, and tall enough that overhead structure matters. A symmetric disk is simultaneously too large in some directions and blind to others, and a uniform margin added to a static footprint shares the same defect.

Two practical consequences motivate this work. First, a disk overestimates the lateral extent of an elongated body, so gaps that the body could pass after aligning its yaw are rejected; the effect is largest for diagonal gaps, where the approach heading and the gap axis differ. Second, symmetric proximity zones trigger safety stops whenever another agent enters a circle around the robot, even when that agent is beside or behind the robot and outside its direction of travel. In mixed-embodiment scenes, where robots of different shapes pass each other in corridors, such spurious stoppages degrade throughput without improving safety.

This paper studies whether embodiment-accurate collision geometry, integrated into a configuration-driven local planner, improves these behaviors and at what computational cost. The contributions are as follows.

1. A configuration-dependent collision set that extends the AgniNav four-parameter envelope to a footprint plus a phase-indexed, speed-dependent leg-swing volume for quadrupeds, a rigid body envelope for wheeled robots, and a full-body capsule with arm reach for humanoids (Section 4.2).
2. An anisotropic clearance cost, a headroom term, and a direction-aware stop zone, each parameterized per embodiment in the body frame (Sections 4.3–4.5).

3. A controlled evaluation in 15 Isaac Lab mixed-embodiment scenes with four embodiments, comparing against symmetric inflation, a static per-embodiment footprint, and a footprint with a fixed swing margin, together with a component ablation (Section 5).
4. An analysis of recorded failure cases showing that the aggregate improvements are small, that the benefit concentrates in specific geometric bottlenecks, and that motion constraints outside the collision set remain a source of near misses (Section 5.6).

02 Related Work

2.1 Configuration-driven cross-embodiment planning

AgniNav [1] is the backbone of this work. It defines an abstract robot configuration consisting of body geometry, sensor placement, and velocity limits, and uses it to run one local planning stack across different embodiments. Its body geometry is a shared four-parameter collision envelope: a collision-relevant height that conditions a monocular image-to-scan predictor, and front length, rear length, and half width that configure collision checking in the local planner. This design makes the robot body a declared input rather than an implicit property of training data, which is the property the present work relies on. The four-parameter envelope is, however, a static rectangle with a height cutoff. It cannot represent volumes that change with gait phase, it treats clearance identically in all directions once the rectangle is fixed, and it has no notion of upper-body reach. The present work keeps the AgniNav configuration interface, perception front end, and candidate-trajectory structure, and replaces only the collision set and clearance terms, so that the effect of geometry can be isolated.

CeRLP [2] is the closest predecessor in spirit. It converts heterogeneous visual observations into a unified geometric representation, including scale-corrected depth and height-adaptive scan abstraction, before local planning. CeRLP addresses observation differences across embodiments, whereas this work addresses the body side of the interface; the two are complementary. EA-Nav [3] conditions a learned navigation policy on embodiment geometry tokens and trains risk-aware corrections on augmented high-risk trajectories. It shows that explicit geometry resolves observation-action ambiguity in learned policies, but its geometry descriptor is a compact vector rather than an articulated or phase-dependent volume. Hu et al. [4] learn adaptive safety margins for visual navigation, adjusting a scalar margin to context. Their result supports the premise that a fixed margin is suboptimal; the present work instead makes the margin structured, directional, and derived from body kinematics rather than learned as a scalar.

2.2 Generalist and embodiment-conditioned navigation policies

GNM [5], ViNT [6], and NoMaD [7] train navigation policies on trajectories pooled from multiple robots, using standardized action spaces and goal-conditioned objectives. These models show that heterogeneous data yields reusable visual priors, but collision avoidance is learned implicitly from the robots in the dataset, so body shapes outside the training range are not represented. RING [8] randomizes body size, rotation pivot, and camera configuration in simulation, and NavFoM [9] trains a single model across quadrupeds, drones, wheeled robots, and vehicles with explicit embodiment and camera identifiers. Both

make embodiment visible to the policy, but neither represents articulated or time-varying collision volumes. The present work is complementary: a generalist policy can supply goals or waypoints, while the geometry layer described here decides near-field feasibility.

2.3 Collision representation in local planning

The dynamic window approach [10] samples admissible velocity commands within acceleration limits and scores forward-simulated arcs by heading, clearance, and speed; its structure underlies many sampling-based local planners, including the candidate rollout used here. EGO-Planner [11] avoids building a full Euclidean signed distance field by computing collision gradients only along the trajectory, which illustrates that collision queries can be made cheap by restricting where they are evaluated. Optimization-based collision avoidance [12] reformulates the distance between a polytopic robot and polytopic obstacles through duality, giving exact non-conservative constraints for non-point bodies, which is the geometric principle behind replacing a disk by a polygon. Voxblox [13] builds signed distance fields incrementally for on-board planning, and is representative of the distance queries assumed in Section 4. For legged robots, Gaertner et al. [14] add collision constraints for the body and legs inside a whole-body model predictive controller, and Grandia et al. [15] formulate perceptive locomotion with terrain-aware constraints in nonlinear MPC. These controllers model leg geometry at the locomotion level; this work brings a reduced version of the same information into the local planner, which runs at a higher level and over a longer horizon.

2.4 Legged and humanoid locomotion and navigation

Learned locomotion controllers for quadrupeds have become robust over rough terrain [16, 17], adapt online to changing dynamics [18], and use egocentric vision for stairs and gaps [19, 20]. Radosavovic et al. [21] demonstrate learned humanoid walking in the real world. These works establish that a velocity-command interface to a learned gait controller is reliable, which is the interface assumed here; they also show that foot trajectories depend on commanded speed, which motivates the speed-dependent swing volume. Rudin et al. [22] and Hoeller et al. [23] learn locomotion and local navigation jointly, and ABS [24] combines an agile policy with a learned reach-avoid recovery policy for high-speed collision-free quadruped motion. In these end-to-end and hybrid systems the collision model is implicit in the reward; the explicit set used here is easier to transfer across bodies because it is computed from kinematic parameters. Traversability estimation [25] is orthogonal: it decides which terrain is passable, while this work decides which free-space regions the body fits through.

2.5 Multi-agent and human-aware navigation

Learning-based multi-agent collision avoidance [27, 28, 29] and crowd-aware navigation [30] treat other agents as disks with fixed radii, which is adequate for homogeneous fleets but not for mixed embodiments. The survey by Mavrogiannis et al. [31] identifies unnecessary stopping and freezing as a recurring failure of conservative planners in shared spaces. The stop-zone construction in Section 4.5 addresses a narrow version of this problem, namely stops triggered by geometry that is beside or behind the robot. AutoRL [26] learns end-to-end navigation behaviors with automatically tuned rewards; it is in-

cluded as a representative of learned point-to-point navigation in which the body enters only through the training simulator.

2.6 Safety filters

Control barrier functions [32], Hamilton-Jacobi reachability [33], and general safety frameworks for learning-based control [34] provide formal guarantees that a system remains in a safe set. Their guarantees are only as good as the safe-set description. An inflated disk produces a valid but conservative safe set; the configuration-dependent set proposed here is tighter and could be used as the constraint set inside such a filter, although this paper does not provide formal guarantees.

2.7 Simulation and evaluation

GPU-parallel simulators [35, 36, 37] make it possible to evaluate many embodiments and seeds at modest cost; the experiments here use Isaac Lab, the successor of Orbit [35]. Domain randomization [38] and the sim-to-real predictivity analysis of Kadian et al. [39] caution that simulator rankings, particularly those involving contact and collision, may not carry over to hardware. Anderson et al. [40] recommend reporting metrics that separate success from path quality; the present evaluation follows that recommendation by reporting geometric, safety, and runtime metrics separately.

03 Problem Formulation

3.1 Embodiment configuration

The robot pose is $x = (p, \theta) \in SE(2)$ with position $p \in \mathbb{R}^2$ and yaw θ , and the commanded velocity is $u = (v_x, v_y, \omega)$; wheeled robots additionally satisfy $v_y = 0$. An embodiment e is described by the AgniNav configuration $c_e^A = (l_f, l_r, w_h, h)$, front length, rear length, half width, and collision height, extended to

$$\mathcal{E}_e = (c_e^A, \mathcal{F}_e, \mathcal{S}_e, \mathcal{H}_e, \Lambda_e, \mathcal{U}_e), \quad (1)$$

where $\mathcal{F}_e \subset \mathbb{R}^2$ is the footprint polygon in the body frame, $\mathcal{S}_e$ is the dynamic-volume model (leg swing or arm reach), $\mathcal{H}_e$ holds vertical extents, Λ_e holds directional clearance parameters, and $\mathcal{U}_e$ holds velocity and acceleration limits. Each element is defined in Section 4.

3.2 Local planning problem

Let $\mathcal{O} \subset \mathbb{R}^3$ be the obstacle set perceived at planning time, including other robots and humans, and let ξ denote embodiment-internal state that changes the occupied volume, such as gait phase. The collision set $\mathcal{B}_e(x, \xi) \subset \mathbb{R}^3$ is the volume occupied by the robot at pose x and internal state ξ . Given a local goal g and the current state, the planner selects a command sequence $u_{0:K-1}$ over horizon K with period Δt that solves

$$\begin{aligned} \min_{u_{0:K-1}} J(\tau) \\ \text{s.t. } x_{k+1} = f_e(x_k, u_k), \quad u_k \in \mathcal{U}_e(u_{k-1}), \quad (2) \\ d_e(x_k, \xi_k; \mathcal{O}) \geq \epsilon_c, \quad k = 1, \dots, K, \end{aligned}$$

where $\tau = (x_{0:K}, u_{0:K-1})$, f_e is the kinematic model of the embodiment, $\mathcal{U}_e(u_{k-1})$ is the admissible command set, $\epsilon_c \geq 0$ is a minimum certified clearance, and

$$d_e(x, \xi; \mathcal{O}) = \min_{o \in \mathcal{O}} \text{sd}(o, \mathcal{B}_e(x, \xi)) \quad (3)$$

is the signed distance from the obstacle set to the collision set, positive outside. The first command u_0 is executed and the problem is re-solved at the next planning cycle.

3.3 Feasible passage width

A gap is a free corridor of width w between two obstacles whose axis makes angle α with the robot's approach direction; diagonal gaps have $\alpha \neq 0$. The planner certifies a gap if Problem (2) has a feasible solution that passes through it. The minimal certified width is

$$w_e^*(\alpha) = \inf\{w : \text{the gap } (w, \alpha) \text{ is certified}\}. \quad (4)$$

For a straight corridor that is long relative to the body, a body with convex planar projection P can traverse it if and only if w exceeds the minimal width of P , $\text{mw}(P) = \min_\phi \text{width}_\phi(P)$, plus $2\epsilon_c$, because the body can be rotated to its narrowest orientation and translated along the corridor axis. For a disk of radius r this gives $2r$, independent of orientation; for a rectangle of half width w_h it gives $2w_h$. The feasible passage width gain reported in Section 5 measures the relative reduction of w_e^* that each planner achieves with respect to a common reference envelope shared by all methods, so that larger values indicate that narrower gaps are certified.

04 Method

4.1 Backbone

The planner inherits three components from AgniNav [1]: the configuration interface, the perception front end that produces an obstacle representation from onboard sensing, and a sampling-based local planner. At each planning cycle the planner draws candidate commands from the dynamic window

$$\mathcal{U}_e(u_{k-1}) = \{u : |u - u_{k-1}| \leq a_e \Delta t, |u| \leq u_e^{\max}\}, \quad (5)$$

with element-wise inequalities, per-axis acceleration limits a_e , and velocity limits $u_e^{\max}$, rolls each candidate forward with f_e over the horizon, discards rollouts that violate the clearance constraint in (2), and selects the rollout with minimum cost. The modifications below change only how $\mathcal{B}_e$, d_e , and the clearance-related cost terms are computed.

4.2 Configuration-dependent collision sets

The collision set is the union of a rigid body part and a dynamic part, both expressed in the body frame and placed in the world by the planar rigid transform $T(x)$:

$$\mathcal{B}_e(x, \xi) = T(x)[\mathcal{B}_e^{\text{body}} \cup \mathcal{B}_e^{\text{dyn}}(\xi)]. \quad (6)$$

Quadrupeds

The rigid part is the trunk prism $\mathcal{B}_e^{\text{body}} = \mathcal{F}_e \times [z_e^{\text{lo}}, z_e^{\text{hi}}]$, where $\mathcal{F}_e$ is the trunk footprint and the vertical interval covers the trunk. The dynamic part is the union of the swept volumes of the four lower legs. Leg i has gait phase $\varphi_i(t) = \varphi^0 + 2\pi f_g t + \psi_i$, with gait frequency f_g and fixed phase offset ψ_i set by the gait (for a trot, diagonal pairs share an offset). During swing, with normalized swing progress $s \in [0, 1]$, the foot position relative to its nominal stance point p_i^{hip} is modeled as

$$r_i(s, v) = \begin{bmatrix} -\frac{1}{2}L(v) \cos(\pi s) \\ \sigma_i \delta_y \\ h_{\text{sw}} \sin(\pi s) \end{bmatrix}, \quad L(v) = v T_{\text{st}}, \quad (7)$$

where $L(v)$ is the step length at forward speed v with stance duration T_{st} , δ_y is the lateral foot offset with side sign $\sigma_i \in \{-1, 1\}$, and h_{sw} is the swing apex height. Stance feet are modeled at r_i evaluated at the end points $s \in \{0, 1\}$. The occupied

volume of leg i at phase φ is the capsule $\text{Cap}(p_i^{\text{knee}}, p_i^{\text{hip}} + r_i, \rho)$ along the shank with radius ρ , where the knee position follows from two-link inverse kinematics. The swing volume over the interval $[t, t + \Delta t]$ is

$$\mathcal{S}_i(\varphi, v) = \bigcup_{\varphi' \in [\varphi, \varphi + 2\pi f_g \Delta t]} \text{Cap}(p_i^{\text{knee}}(\varphi'), p_i^{\text{hip}} + r_i(s(\varphi'), v), \rho), \quad (8)$$

where $s(\varphi')$ is the swing progress at phase φ' , and $\mathcal{B}_e^{\text{dyn}}(\xi) = \bigcup_{i=1}^4 \mathcal{S}_i(\varphi_i, v)$ with $\xi = (\varphi^0, v)$.

Because gait phase cannot be predicted reliably far into the future, phase indexing is used only for the first gait cycle of the rollout, $t \leq 1/f_g$. Beyond that, the phase-agnostic envelope $\mathcal{S}_i(v) = \bigcup_{\varphi} \mathcal{S}_i(\varphi, v)$ is used. This choice keeps near-term checks tight, where they determine whether a gap is entered, while remaining conservative for later rollout steps that are re-planned anyway. The model in (7) makes the swing excursion mostly fore-aft and proportional to speed, with a small lateral component; consequently the swing volume enlarges the minimal width of the projected body much less than it enlarges its length, which is the geometric mechanism behind the diagonal-gap results.

Wheeled rover

The rover has no internal state that changes its envelope, so $\mathcal{B}_e^{\text{dyn}} = \emptyset$ and $\mathcal{B}_e^{\text{body}} = \mathcal{F}_e \times [0, h_e]$ with $\mathcal{F}_e$ the rectangle defined by (l_f, l_r, w_h) . This coincides with the AgniNav envelope. The rover's non-holonomic constraint is a motion constraint enforced through f_e and $\mathcal{U}_e$; it is not part of the collision set (Section 6).

Humanoid

The humanoid body is a vertical capsule of radius r_t spanning ground to head height h_e , $\mathcal{B}_e^{\text{body}} = \text{Cap}((0, 0, r_t), (0, 0, h_e - r_t), r_t)$, augmented by two arm-reach capsules $\mathcal{A}_j(\xi) = \text{Cap}(p_j^{\text{sh}}, p_j^{\text{sh}} + \ell_a n_j(\xi), \rho_a)$ for $j \in \{L, R\}$, with shoulder positions p_j^{sh} , arm length ℓ_a , arm radius ρ_a , and arm direction $n_j(\xi)$ swept over the arm-swing range that the locomotion controller produces at the current speed. Thus $\mathcal{B}_e^{\text{dyn}}(\xi) = \mathcal{A}_L(\xi) \cup \mathcal{A}_R(\xi)$. At foot level the set is narrow; at shoulder level it is wide; and its height is used by the headroom term below.

4.3 Anisotropic clearance cost

The hard constraint in (2) certifies feasibility; the clearance cost ranks feasible rollouts by how comfortably they clear obstacles. For an obstacle point o near pose x_k , let $\delta = R(\theta_k)^\top (o_{xy} - p_k)$ be its planar offset in the body frame and $\beta = \text{atan2}(\delta_y, \delta_x)$ its bearing. The directional decay length is

$$\lambda_e(\beta, v) = \lambda_f(v) [\cos \beta]_+^2 + \lambda_r [-\cos \beta]_+ + \lambda_s \sin^2 \beta, \quad (9)$$

with $[a]_+ = \max(a, 0)$, rear and side decay lengths λ_r and λ_s , and a front decay length that grows with speed,

$$\lambda_f(v) = \lambda_f^0 + t_h v, \quad (10)$$

where t_h is a time headway. The interpolation in (9) is continuous in β and reduces to an isotropic cost when $\lambda_f = \lambda_r = \lambda_s$. The clearance cost of a rollout is

$$J_{\text{clr}}(\tau) = \sum_{k=1}^K \sum_{o \in \mathcal{N}(x_k)} \exp\left(-\frac{[\text{sd}(o, \mathcal{B}_e(x_k, \xi_k))]_+}{\lambda_e(\beta_o, v_k)}\right), \quad (11)$$

where $\mathcal{N}(x_k)$ is the set of obstacle points within a query radius. Distances are measured to the collision set rather than to the robot center, so the cost does not double-count the body extent, and the decay lengths encode only the desired clearance beyond the body. The parameters $\Lambda_e = (\lambda_f^0, t_h, \lambda_r, \lambda_s)$ are set per embodiment: quadrupeds and the rover use a short side length, since lateral contact at low relative speed is the least consequential, whereas the humanoid uses a longer side length to account for arm swing that is not captured exactly by $\mathcal{A}_j$.

4.4 Headroom term

For humanoids, overhead structure such as shelves, pipes, or a passing robot's raised component can intersect the head or arms even when the floor-level footprint is free. Let z_g be the local ground height and η_e a vertical margin. The headroom cost penalizes overhead obstacle points within the planar reach radius r_e^{reach} , where $\mathbf{1}[\cdot]$ is the indicator function:

$$J_{\text{head}}(\tau) = \sum_{k=1}^K \sum_{o \in \mathcal{N}(x_k)} \mathbf{1}[\|\delta_o\| \leq r_e^{\text{reach}}] \cdot [h_e + \eta_e - (o_z - z_g)]_+^2, \quad (12)$$

with δ_o the planar body-frame offset of o and o_z its height. Points with $o_z - z_g < h_e$ that intersect $\mathcal{B}_e$ are already excluded by the hard constraint; the quadratic term shapes behavior in the margin band $[h_e, h_e + \eta_e]$. For quadrupeds and the rover the term is inactive because their collision height is below typical overhead structure; the AgniNav height parameter h already handles obstacles below that height.

4.5 Direction-aware stop zone

In addition to the planner, each embodiment runs a proximity monitor that commands a stop if another agent or obstacle enters a stop zone. The symmetric baseline uses a disk of radius $r_e + \epsilon_s + d_b(v)$, where r_e is the circumscribed radius, ϵ_s a fixed margin, and

$$d_b(v) = \frac{v^2}{2a_e^{\text{brk}}} + v t_{\text{lat}} \quad (13)$$

is the braking distance with braking deceleration a_e^{brk} and reaction latency t_{lat} . The proposed stop zone is the set of body-frame points

$$\mathcal{Z}_e(\xi, v) = \{\delta : \text{sd}(\delta, \mathcal{B}_e^{xy}(\xi)) \leq \epsilon_s + d_b(v) [\cos \beta_\delta]_+\}, \quad (14)$$

where $\mathcal{B}_e^{xy}$ is the planar projection of the collision set restricted to the vertical extent of the intruding object. Braking distance is added only in the direction of travel, and lateral distance is measured to the actual body rather than to a circumscribed circle. When a wheeled robot passes beside a humanoid, it may enter the symmetric disk without entering $\mathcal{Z}_e$, and no stop is issued.

4.6 Total cost and planning loop

The rollout cost is

$$J(\tau) = w_g J_{\text{goal}} + w_c J_{\text{clr}} + w_h J_{\text{head}} + w_s J_{\text{smooth}}, \quad (15)$$

where J_{goal} is the AgniNav goal-progress term, $J_{\text{smooth}} = \sum_k \|u_k - u_{k-1}\|_W^2$ penalizes command changes with weight matrix W , and $w_g, w_c, w_h, w_s \geq 0$ are scalar weights. One planning cycle proceeds as follows.

1. Update $\mathcal{O}$ from perception and read the current pose, velocity, and, for legged embodiments, gait phase φ^0 from the locomotion controller.
2. Sample candidate commands from $\mathcal{U}_e(u_{-1})$ in (5) and roll each forward with f_e .
3. For each rollout step, run a broad-phase test against the bounding disk of $\mathcal{B}_e$; obstacle points outside it are skipped.
4. For remaining points, compute $\text{sd}(o, \mathcal{B}_e)$ using precomputed swing volumes (below); discard the rollout if any distance is below ϵ_c .
5. Evaluate (15) on surviving rollouts, execute the first command of the minimizer, and evaluate the stop zone (14) in parallel at the control rate.

4.7 Efficient evaluation and design choices

Evaluating (8) online would require inverse kinematics inside every rollout. Instead, the planar projections of $\mathcal{S}_i(\varphi, v)$ and $\tilde{\mathcal{S}}_i(v)$ are precomputed offline on a grid of phase bins and speeds for each legged embodiment and stored as convex polygons; at run time the planner looks up the nearest bin and computes polygon distances. The humanoid arm capsules are tabulated by speed in the same way. This turns the dynamic part of the collision set into table lookups plus convex distance queries of the same type already used for the static footprint.

Three design choices deserve justification. First, swing volumes are swept over one planning period, as in (8), rather than evaluated at instants, so that a rollout cannot pass a thin obstacle between two sampled phases. Second, the phase-agnostic envelope beyond one gait cycle trades tightness for robustness to phase drift between the planner’s prediction and the locomotion controller. Third, the anisotropic cost (9) is applied as a soft term rather than by enlarging the hard constraint, because enlarging the hard constraint directionally would reproduce the conservatism of a fixed margin, which the baseline in Section 5.2 isolates.

05 Experiments

5.1 Setup

All experiments are run in Isaac Lab mixed-embodiment scenes. The benchmark consists of 15 scenes that contain diagonal gaps with angles between 45 and 75 degrees, cluttered corridors, and multi-robot proximity situations in which robots of different embodiments share space. Four embodiments are evaluated: a Go2-class quadruped, a B2-class quadruped, a six-wheeled rover, and a 12-DoF humanoid. Each configuration is run with 5 seeds and 30 episodes each. The collision sets are instantiated as in Section 4.2: footprint plus dynamic leg-swing volume for the two quadrupeds, a body envelope for the rover, and a full-body capsule with arm reach for the humanoid.

5.2 Baselines

All methods share the AgniNav backbone, perception, candidate sampling, and goal term, and differ only in the collision geometry and clearance terms.

- **Symmetric inflation.** Every embodiment is represented by a disk with its circumscribed radius plus a margin; clearance cost is isotropic.
- **Per-embodiment static footprint.** Each embodiment uses its static footprint polygon with isotropic clearance; no swing volume, arm reach, or headroom term.
- **Footprint with fixed 10 cm swing margin.** The static footprint is dilated uniformly by 10 cm to approximate leg swing, with isotropic clearance.
- **Ours.** Configuration-dependent collision sets, anisotropic clearance cost, headroom term, and direction-aware stop zone.

5.3 Metrics

Feasible passage width gain is the relative reduction, in percent, of the minimal certified gap width w_e^* in (4), measured against the same reference envelope for every method and aggregated over gap scenes and embodiments. Collision rate is the number of collisions per kilometer traveled. Planner runtime is the 95th percentile of the wall-clock time of one planning cycle. Spurious stoppages are stop-zone activations per episode in which no collision would have occurred had the robot continued, as determined by the scene’s ground-truth geometry.

5.4 Main results

Table 1 reports the main comparison. The proposed planner obtains the highest feasible passage width gain, 14.8%, compared with 14.2% for symmetric inflation, 14.0% for the static footprint, and 12.9% for the footprint with a fixed swing margin. The difference to the strongest baseline is 0.6 percentage points. The collision rate is 0.18 per km against 0.19 per km for the first two baselines and 0.20 per km for the fixed-margin baseline, a difference of 0.01 per km to the best baseline. The p95 planner runtime is 6.4 ms, which is 0.5 ms lower than symmetric inflation (6.9 ms) and 0.8 ms lower than the fixed-margin variant (7.2 ms). Spurious stoppages are 0.3 per episode for all four methods.

These aggregate differences are small. The results file records point estimates without dispersion across seeds, so the differences of 0.6 percentage points in width gain and 0.01 per km in collision rate cannot be assessed for statistical significance here, and they should be read as consistent with, rather than proof of, an improvement. Two observations are nevertheless robust to this caveat. First, the fixed-margin baseline is worst on width gain, collision rate, and runtime, which indicates that approximating leg swing with a uniform dilation is not merely neutral but counterproductive: the dilation enlarges the minimal width of the body by 20 cm, whereas the modeled swing volume extends mainly in the fore-aft direction. Second, the static footprint does not outperform symmetric inflation in aggregate (14.0% versus 14.2%), so the gain of the proposed planner is not explained by replacing a disk with a polygon alone.

The lower runtime of the proposed planner is plausibly due to the broad-phase test against a tighter bounding region combined with tabulated swing polygons, which reduce the num-

Table 1: Main comparison across 15 Isaac Lab mixed-embodiment scenes, four embodiments, 5 seeds, and 30 episodes each. Higher is better for passage width gain; lower is better for the other columns.

Method	Feasible passage width gain (%)	Collision rate (per km)	Planner runtime p95 (ms)	Spurious stoppages (per episode)
Symmetric inflation (all embodiments as blobs)	14.2	0.19	6.9	0.3
Per-embodiment static footprint only	14.0	0.19	7.0	0.3
Footprint + fixed 10 cm swing margin	12.9	0.20	7.2	0.3
Ours	14.8	0.18	6.4	0.3

Table 2: Ablation of the proposed planner on feasible passage width gain.

Variant	Feasible passage width gain (%)
Ours (embodiment-accurate geometry)	14.8
w/o leg-swing volume	13.4
w/o headroom term (humanoid)	13.7
w/o anisotropic clearance cost	13.9

ber of narrow-phase distance queries relative to a large inflated disk; this explanation was not isolated by profiling in this study.

The unchanged aggregate spurious-stoppage rate means that the benchmark-level claim of fewer spurious stoppages is not supported by Table 1. The effect of the direction-aware stop zone is visible only in the specific humanoid-rover corridor case discussed in Section 5.6, which is diluted in the average over all scenes and embodiments.

5.5 Ablation

Table 2 removes one component at a time. Removing the leg-swing volume reduces the width gain from 14.8% to 13.4% (1.4 percentage points), removing the humanoid headroom term reduces it to 13.7% (1.1 points), and removing the anisotropic clearance cost reduces it to 13.9% (0.9 points).

All three ablated variants fall below symmetric inflation (14.2%) and below the static footprint (14.0%). The component contributions are therefore not additive: the individual drops sum to 3.4 percentage points, whereas the full method exceeds the static-footprint baseline by only 0.8 points. A consistent interpretation is that the components are coupled. Without the swing volume, the anisotropic cost uses short lateral decay lengths around a body that is modeled as smaller than it is, and the hard constraint must reject more candidates late in the rollout; without the anisotropic cost, the tighter collision set produces rollouts that pass close to obstacles in directions where clearance is valuable, which the isotropic cost then penalizes uniformly. Under this reading, partial geometric fidelity can be worse than a simple consistent approximation, and the embodiment-accurate geometry pays off only when the collision set and clearance cost are modeled together. That the headroom term, which is active only for the humanoid, affects the aggregate width gain also indicates that the humanoid scenes contribute a substantial share of the aggregate. A per-embodiment breakdown would be needed to confirm these interpretations.

5.6 Failure cases and qualitative analysis

Table 3 summarizes the recorded failure cases.

Diagonal gap

The headline case is a 60 degree diagonal gap of width 71 cm. With symmetric inflation, the quadruped fails 12 of 30 attempts, a failure rate of 40%. With the leg-swing geometry,

the quadruped threads the gap at 1.2 m/s with 8 cm clearance. The mechanism follows from Section 3: the disk’s minimal width equals its diameter regardless of yaw, whereas the footprint-plus-swing set has a minimal width close to the trunk-plus-lateral-foot width when the robot yaws to align with the gap axis, and the fore-aft swing excursion of (7) does not enter the minimal width. The 8 cm clearance at 1.2 m/s shows that the tighter set did not require slowing to a crawl. Because the success count of the proposed planner across the 30 attempts in this gap is not recorded in the collected results, the case establishes that the gap becomes traversable rather than quantifying a success rate.

Humanoid near a wheeled robot

In corridor 4, a humanoid using the static footprint produces 3.1 spurious stoppages per episode as a wheeled robot passes, and the full-body model reduces this to 0.4, a reduction of 2.7 stoppages per episode, or 87%. The static footprint models neither the narrowness of the humanoid at foot level nor the direction of travel, so the rover’s lateral pass triggers a stop. With the full-body model and the stop zone (14), lateral proximity at foot level is measured against the actual capsule and does not add braking distance. This is the scenario that motivated the stop-zone design. As noted above, the aggregate stoppage rate in Table 1 is identical across methods, so this improvement is local to scenes with this configuration.

Rover differential constraint

In scene 11, one near miss of the rover is attributed to its differential-drive constraint. The collision set describes where the body is, not which motions are possible; a rover that must swing its rear end through a turn can approach obstacles in ways that the instantaneous collision check at each rollout step does not anticipate if the rollout’s turning model is approximate. This is a motion-constraint issue and is outside the scope of the geometry layer, but it shows that collision geometry alone does not capture all embodiment-specific hazards.

06 Limitations

The evaluation is entirely in simulation. Leg-swing volumes depend on the locomotion controller, and the swing model in (7) is a parametric approximation; on hardware, foot trajectories vary with terrain, slip, and disturbance recovery, and the sim-to-real caveats of [39] apply with particular force to contact-level geometry. The results report point estimates without dispersion across seeds, so small aggregate differences cannot be tested for significance. The aggregate improvements are modest, the aggregate spurious-stoppage rate does not change, and the ablation shows that partial versions of the method underperform simple baselines, which limits the method’s robustness to misconfiguration. Per-embodiment and per-scene breakdowns, beyond the recorded case studies, are not available. The collision set excludes motion constraints such as the rover’s differ-

Table 3: Recorded failure cases and case studies.

Case	Observation	Interpretation
60 deg diagonal gap at 71 cm (quadruped)	Symmetric-inflation quadruped fails 12/30; with leg-swing geometry it threads the gap at 1.2 m/s with 8 cm clearance	Disk overestimates minimal width; swing volume extends fore-aft, not laterally
Humanoid near a wheeled robot, corridor 4	Static-footprint humanoid: 3.1 spurious stoppages per episode; full-body model: 0.4	Symmetric proximity triggers on lateral passes; direction-aware zone does not
Rover near-miss, scene 11	One near miss attributed to the differential constraint	Motion constraint, not geometry; outside the collision set by design

ential drive, which produced a recorded near miss. Gait phase is assumed to be readable from the locomotion controller; for black-box controllers it would have to be estimated. Finally, the stop-zone construction assumes that other agents' extents are perceived correctly; perception error in the extent of other robots was not studied.

07 Conclusion

This paper extended the AgniNav configuration-driven local planner with embodiment-accurate collision geometry: a configuration-dependent collision set with phase-indexed leg swing for quadrupeds, a body envelope for rovers, and a full-body capsule with arm reach and headroom for humanoids, together with an anisotropic clearance cost and a direction-aware stop zone. In 15 Isaac Lab mixed-embodiment scenes with four embodiments, the method achieved a feasible passage width gain of 14.8% against 14.2% for symmetric inflation, a collision rate of 0.18 against 0.19 per km, and a p95 runtime of 6.4 against 6.9 ms, with unchanged aggregate spurious stoppages. The aggregate effect is small; the clearest benefits appear in specific geometric bottlenecks, where a quadruped that fails 12 of 30 attempts under symmetric inflation threads a 71 cm diagonal gap at 1.2 m/s, and where a humanoid's spurious stoppages near a wheeled robot fall from 3.1 to 0.4 per episode. A uniform swing margin performs worse than either a disk or a static footprint, which suggests that if collision geometry is refined, it should be refined in the directions where the body actually extends. Future work should report seed-level dispersion and per-embodiment breakdowns, incorporate motion constraints such as differential drive into feasibility checking, and validate the swing model on hardware.

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