

PASSAGE: Scaling Scene-Aligned Motion Learning for Perceptive Humanoid Traversal in Cluttered Environments

Yuxuan Ma^{1,*}, Zicheng Zeng^{1,2,3,*}, Chunlin Peng^{1,4,5,*}, Zhoujian Li^{1,6},
Zetong Zhao^{1,7}, Zhikai Zhang^{1,7}, Yunrui Lian^{1,7}, Han Xue^{1,7}, Sikai Liang^{1,7},
Weiyi Zhu¹, Mulin Chen^{1,7}, Chenghuai Lin¹, Jiayu Zeng¹, Yanwei An¹,
Songan Zhang⁵, Jiayuan Gu³, Jilong Wang¹, Jingbo Wang¹, He Wang^{1,8}, and Li Yi^{1,2,7,†}
¹Galbot ²Shanghai Qi Zhi Institute ³ShanghaiTech University ⁴Zhongguancun Academy
⁵Shanghai Jiao Tong University ⁶National University of Singapore ⁷Tsinghua University ⁸Peking University
*Equal contribution [†]Corresponding author

Project page: <https://galaxygeneralrobotics.github.io/PASSAGE/>



Fig. 1: PASSAGE enables a humanoid robot to traverse cluttered environments with whole-body behaviors using only onboard perception. (a) Multi-exposure composite of the robot stepping over a wooden pallet, ducking under a block archway, and squeezing past a wheeled case. (b) A cluttered test scene with the robot’s poses overlaid along the traversed path. (c) Stepping over a low barrier in a furnished living space. (d) Ducking under a hanging curtain to pass through a doorway. All behaviors are produced by a single planner and tracker learned from scene-aligned human demonstrations, without prebuilt maps or offboard computation.

Abstract—Humanoid robots can step over, squeeze past, and duck under obstacles, but learning to select and coordinate these behaviors from onboard perception remains challenging. Many existing approaches rely on task-specific reinforcement-learning objectives or curated motion libraries, making broad behavioral coverage costly. We present PASSAGE, a perception-conditioned planner–tracker framework for humanoid traversal. Using virtual reality and inertial motion capture, we collect 100 h of scene-aligned human motion across 1,500 cluttered scenes. A conditional flow-matching planner generates short-horizon references from motion history, a local destination, and a robot-centric multi-layer elevation map, while a perceptive whole-body tracker executes them at 50 Hz with geometric feedback. Real-time chunking promotes inter-chunk consistency, and planner-side RL post-training under the frozen tracker further improves closed-loop performance. Without skill annotations or obstacle-specific policies, one planner–tracker pair selects and composes traversal behaviors across unseen geometries. In simulation, component ablations quantify the contribution of each stage. Across three independent training seeds, scaling captured data from 6 to 100 h increases mean contact-free success from 48.1% to 68.9% on held-out

scenes, while the final model with validated scene augmentation reaches 70.3%. The fully onboard system integrates egocentric 3D LiDAR perception, online occupancy mapping, 6.25-Hz planning, and 50-Hz control on a Jetson AGX Orin; tests across 50 unseen physical layouts demonstrate traversal without prebuilt maps or offboard computation.

I. INTRODUCTION

Humanoid robots can exploit whole-body articulation to traverse clutter by stepping over low obstacles, turning sideways through narrow openings, ducking under overhangs, or combining these behaviors. This requires a robot to select and coordinate motions from onboard geometry and execute them despite perception and tracking errors. Learning such a unified repertoire at scale remains challenging.

Recent perceptive methods acquire traversal behaviors primarily through reinforcement learning (RL). CAT [1], for example, trains scene-specific specialists with body-part-level collision guidance from HumanoidPF and distills them into a generalist. Although effective in clutter, this

pipeline requires manually specified locomotion objectives and computationally intensive specialist training; its reported controller actuates only 12 leg joints, limiting the scope of whole-body coordination. Motion-data approaches [2], [3] provide richer whole-body priors, but scalable behavior selection in clutter requires demonstrations aligned with the surrounding geometry.

Wang et al. [4] introduced a virtual-reality-based framework and collected 2.3 h of such demonstrations across 145 procedurally generated environments, focusing on data collection and benchmarking. These works leave two questions: how can scene-aligned demonstrations support a unified, closed-loop perception–planning–control system for diverse traversal, and how does demonstration scale affect motion generation and downstream execution?

We address both questions with PASSAGE, a scalable framework for perceptive whole-body humanoid traversal. Using a virtual-reality interface and inertial motion capture, we collect 100 h of scene-aligned human demonstrations across 1,500 procedurally generated cluttered scenes. A conditional flow-matching planner generates short-horizon references from motion history, a local destination, and robot-centric multi-layer elevation maps. Real-time chunking (RTC) promotes inter-chunk consistency, while planner-side RL post-training under the frozen tracker further improves closed-loop performance. A perception-enhanced ScaleBFM tracker [5] executes the references using high-frequency geometric feedback. The same planner–tracker pair thereby selects and composes traversal behaviors across unseen geometries without skill annotations or obstacle-specific policies. We further quantify how captured scene-aligned data scale relates to closed-loop goal reaching and collision avoidance across three independent training seeds under a fixed planner architecture, tracker checkpoint, training budget, and evaluation protocol. Onboard 3D LiDAR and online occupancy mapping produce egocentric elevation observations, and the complete stack runs on an NVIDIA Jetson AGX Orin.

Our contributions are:

- **Unified Perceptive Traversal.** We couple a flow-matching planner with a perception-enhanced whole-body tracker. RTC and planner-side RL post-training under a frozen tracker improve closed-loop execution, enabling the same pair to select, compose, and execute traversal behaviors without skill annotations or obstacle-specific policies.
- **Scene-Aligned Data Scaling.** Under a fixed architecture, training budget, tracker checkpoint, and evaluation protocol, we train planners with three independent seeds on each nested subset from 6 to 100 h and observe a robust positive empirical trend in closed-loop goal reaching and collision avoidance on held-out scenes.
- **Scalable Data Acquisition.** Our virtual-reality-guided inertial motion-capture pipeline combines procedural scene generation, retargeting, and MuJoCo-based kinematic collision validation, yielding 100 h of demonstrations across 1,500 cluttered scenes.
- **Fully Onboard Deployment.** We integrate egocentric

3D LiDAR perception, online mapping, planning, and control onboard the robot and validate traversal across 50 unseen physical layouts without prebuilt maps or offboard resources.

II. RELATED WORK

A. Whole-Body Control and Perceptive Locomotion

Following DeepMimic [6], generalist whole-body trackers reproduce diverse references with one policy [7], [8], [9], [10], [11]. They broaden the executable repertoire but neither choose future motion nor ensure geometric compatibility.

Perceptive controllers condition execution on environmental observations. KiVi [12] separates proprioceptive and visual pathways for robustness to visual corruption; TAGA [13] learns terrain-aware attention; and Perceptive BFM [14] grounds prescribed references in local terrain. For traversal, CAT [1] distills HumanoidPF-guided specialists through DAGger; Gallant [15] and PHP [2] learn goal-conditioned and skill-compositional perceptive policies, respectively. Light-LoCo-Parkour [16] distills multiple skills into one depth-conditioned policy that autonomously selects behaviors without reference inputs, skill labels, or runtime motion graphs. Prior systems thus learn behavior through simulator objectives, compose curated skill libraries, or adapt supplied references; PASSAGE instead learns destination-conditioned future motion from long-horizon, scene-aligned demonstrations.

B. Scene-Aligned Data and Motion Generation

Scene-aligned data supervise geometry-conditioned behavior. VideoMimic [17] reconstructs motion and geometry from monocular video and distills an environment-conditioned controller. EgoHTR [18] reconstructs terrain-traversal demonstrations from egocentric wearables and portable scans, validated with clip-specific perceptive trackers. Moving Through Clutter [4] collects 2.3 h across 145 procedural scenes as a data benchmark. PASSAGE scales virtual-reality-guided inertial capture to 100 h across 1,500 scenes and studies the empirical relationship between captured-data scale and closed-loop traversal.

Generative models bridge navigation and whole-body control. BeyondMimic [19] guides diffusion at inference using differentiable task costs. RLPF [20] fine-tunes a text-conditioned generator with tracker-derived physical feedback; GenTrack [21] alternates execution-grounded generator alignment and tracker training. Zhang *et al.* [3] train a terrain-conditioned diffusion generator and an RL tracker separately, then adapt the tracker in closed loop with the generator fixed. PASSAGE instead pairs its destination-conditioned flow-matching planner with a separately trained perceptive general tracker, requiring no planner–tracker co-training; with the tracker frozen, planner-side RL post-training further improves closed-loop traversal.

III. PASSAGE FRAMEWORK

PASSAGE separates geometry-conditioned motion generation from dynamic whole-body execution. At each replanning step, a destination-conditioned flow-matching planner

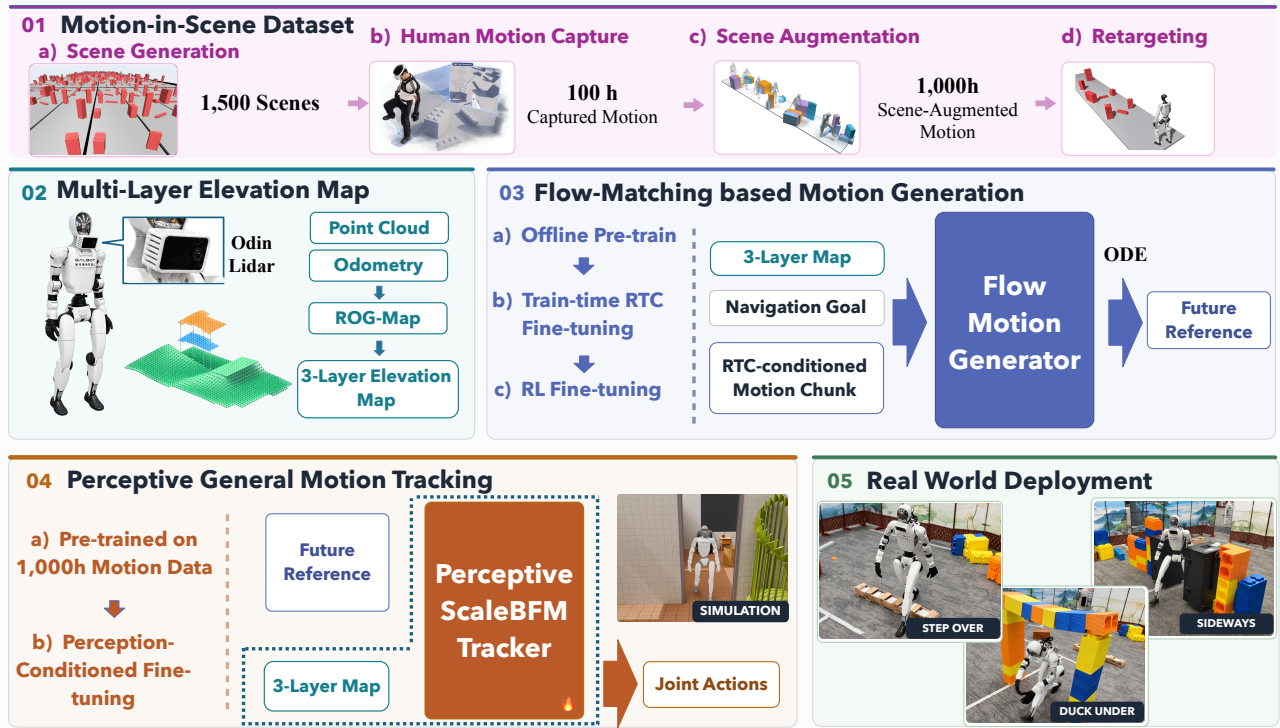


Fig. 2: Slow-fast plan-and-control architecture: the flow-matching planner (6.25 Hz) outputs reference motions from the elevation map, and the perceptive controller (50 Hz) executes them at the joint level.

generates a short-horizon kinematic reference from recent motion and robot-centric geometry. A perception-enhanced ScaleBFM tracker [5] executes the reference at 50 Hz through its general whole-body tracking interface. The planner and tracker are initially trained independently. The planner can roll out kinematic motion on its own; for dynamic execution, its outputs are deterministically converted into the reference representation consumed by the tracker. The tracker is trained with dataset references rather than planner outputs. During closed-loop post-training, the tracker remains frozen and only the planner is updated through tracker-executed rollouts. This design requires neither joint end-to-end optimization nor behavior-specific controllers.

A. Scene-Aligned Demonstrations at Scale

Procedural scenes. Using the procedural scene generator, we populate 10 m corridors with composable block obstacles. Eight difficulty variables— x -step, lateral deviation, passage length and width, ceiling probability and height, and floor probability and height—are sampled and composed along each corridor to cover ground-level, lateral, and overhead constraints.

VR-guided motion capture. Operators wearing a Noitom PN Link inertial motion-capture suit and a virtual reality (VR) headset traverse the generated scenes from an egocentric view (Fig. 3). Collisions between the virtual body and the scene trigger haptic feedback, and the corresponding demonstrations are rejected. Operators are encouraged to vary both their motions and traversal strategies. We retarget

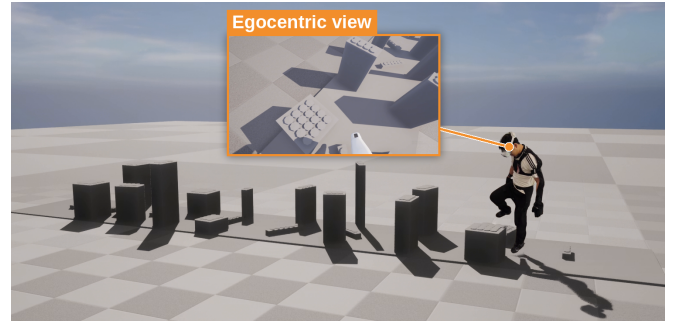


Fig. 3: VR-guided scene-aligned motion capture. An operator wearing an inertial motion-capture suit traverses a procedural scene from the avatar’s egocentric view (inset).

the recordings [22], [23] to a 29-degree-of-freedom (DoF) Unitree G1 and scale the corresponding scenes to preserve motion-geometry alignment. After collision rejection and quality screening, we retain 19,310 sequences, 17,470,128 frames, totaling approximately 100 h across 1,500 scenes.

Validated scene augmentation. Since motion and scene geometry are stored separately, retargeting and augmentation are independent and may be applied in either order. For each motion, we generate ten obstacle variants with scales in $[0.5, 1.5]$ and rotations within $\pm 15^\circ$, uniformly scale them to match the retargeted motion, and retain only collision-free pairs under kinematic replay in MuJoCo. These validated variants expand the 100 h corpus to approximately 1,000 h

of motion–scene training pairs; up to 30 background layouts per scene and online left–right mirroring ($p = 0.5$) further diversify the geometry during training.

B. Modular Planner–Tracker Architecture

1) *Perception-Conditioned Flow Planner: Motion and conditioning.* We use the following 50 Hz representation for motion frame i :

$$\mathbf{s}_i = [h_i, (\mathbf{g}_i^b)^\top, (\mathbf{v}_{i,xy}^n)^\top, \omega_{i,z}^n, \mathbf{q}_i^\top, \dot{\mathbf{q}}_i^\top]^\top \in \mathbb{R}^{65}, \quad (1)$$

where h_i is the root height; $\mathbf{g}_i^b$ is gravity expressed in the root frame and encodes root tilt but not yaw; $\mathbf{v}_{i,xy}^n$ and $\omega_{i,z}^n$ are the planar root velocity and yaw rate in a yaw-aligned navigation frame; and $\mathbf{q}_i, \dot{\mathbf{q}}_i$ are the positions and velocities of the 29 actuated joints. Given four history frames $\mathbf{H}_i = [\mathbf{s}_{i-3}, \dots, \mathbf{s}_i]$, the planner predicts $H = 25$ future frames, or 0.5 s of motion. It is additionally conditioned on a robot-centric destination $\mathbf{c}_g$ and a torso-centered three-layer elevation map $\mathbf{E}_i \in \mathbb{R}^{3 \times 31 \times 61}$ that jointly encodes supporting surfaces, lateral obstructions, and overhead clearance.

Conditional flow matching. We adapt a transformer backbone [24], [25] to jointly process terrain, destination, history, noisy-motion, and flow-time tokens. Let $\tilde{\mathbf{Y}} \in \mathbb{R}^{H \times 65}$ be a normalized ground-truth motion chunk, $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, and $t \sim \mathcal{U}(0, 1)$. Using the convention that $t = 0$ denotes data and $t = 1$ denotes noise, we define

$$\mathbf{X}_t = (1 - t)\tilde{\mathbf{Y}} + t\epsilon, \quad \mathbf{u}^* = \epsilon - \tilde{\mathbf{Y}}. \quad (2)$$

Let $\mathcal{C} = (\mathbf{H}, \mathbf{E}, \mathbf{c}_g)$ denote the conditioning inputs. The flow-matching objective is

$$\mathcal{L}_{\text{FM}} = \mathbb{E} \left[\frac{1}{65H} \sum_{j,k} \rho(v_{\theta,jk}(\mathbf{X}_t, t; \mathcal{C}) - u_{jk}^*) \right], \quad (3)$$

where the sum spans $j = 1, \dots, H$ and $k = 1, \dots, 65$, and ρ is the smooth- L_1 loss. At inference, generation starts from Gaussian noise and integrates the learned vector field from $t = 1$ to $t = 0$.

Motion and geometry regularization. We form the denoised estimate

$$\hat{\mathbf{Y}} = \mathbf{X}_t - t v_\theta(\mathbf{X}_t, t; \mathbf{H}, \mathbf{E}, \mathbf{c}_g), \quad (4)$$

and decode it through differentiable forward kinematics. Auxiliary losses regularize root-state and joint-velocity reconstruction, position–velocity finite-difference consistency, foot sliding, body-keypoint jerk, and oriented-box penetration. We additionally precompute HumanoidPF guidance [1] from the scene signed-distance field and destination, and sample it at 11 anchors on the pelvis, torso, head, shoulders, palms, knees, and feet. The resulting loss $\mathcal{L}_{\text{PF}}$ repels anchors within 0.20 m of obstacles and penalizes anchor motion opposing the local guidance direction. HumanoidPF is used only for training and adds neither planner observations nor runtime computation. The complete pre-training objective is

$$\begin{aligned} \mathcal{L}_{\text{pre}} = & \mathcal{L}_{\text{FM}} + 2\mathcal{L}_{\text{root}} + 2\mathcal{L}_{\text{jvel}} + 0.05\mathcal{L}_{\text{fd}} + 0.02\mathcal{L}_{\text{slide}} \\ & + 0.05\mathcal{L}_{\text{jerk}} + 5\mathcal{L}_{\text{box}} + \mathcal{L}_{\text{PF}}. \end{aligned} \quad (5)$$

2) *Perception-Enhanced General Tracker:* We use the whole-body interface of ScaleBFM [5], pre-trained on a separate 1,000 h general-motion corpus for a 29-DoF G1 carrying the AGX backpack. ScaleBFM uses proprioception–action tokens as cross-attention queries and motion-reference tokens as keys and values. We append eight terrain tokens encoded by a convolutional neural network (CNN) to its motion-reference token sequence, without changing the architecture of the pretrained transformer or action head. At 50 Hz, the tracker maps three-frame proprioceptive and action histories and references for 14 body links to 29-dimensional residual joint-position commands.

We adapt the tracker with asymmetric actor–critic proximal policy optimization (PPO), using whole-body tracking objectives together with safety and smoothness regularization. We first optimize the terrain encoder and critic for 200 iterations and then fine-tune the complete policy with dynamics, observation, and external-perturbation randomization. This adaptation uses reference motions from the scene-aligned dataset, not planner-generated rollouts. The resulting general tracking interface therefore accepts the planner’s references directly, without behavior-specific experts or joint planner–tracker optimization.

C. Planner-Side Refinement

1) *Real-Time Chunking:* Independent receding-horizon samples may become discontinuous at chunk boundaries. We therefore adopt the action-prior denoising of Soft RTC [26], extending hard training-time conditioning [27]. We sample $d \in \{0, \dots, 4\}$ with $p(d = k) \propto e^{-k}$ and set $e_d = \min\{H, 5, \lceil 2d \rceil\}$. For token j , we define

$$\begin{aligned} w_j(d) &= \text{clip}_{[0,1]} \left(\frac{e_d - j + 1}{e_d - d + 1} \right), \\ a_j &= 1 - w_j(d), \quad \tau_j = a_j t, \\ \mathbf{X}_{\tau,j} &= (1 - \tau_j)\tilde{\mathbf{Y}}_j + \tau_j \epsilon_j. \end{aligned} \quad (6)$$

Here, $\text{clip}_{[0,1]}$ implements the endpoint-excluding linear taper. Ground-truth states provide the training prior, leaving committed tokens clean, transition tokens partially corrupted, and future tokens under standard flow matching. At inference, the aligned suffix of the previous chunk provides the prior under the same token-wise blending rule. We weight token j in Eq. (3) by a_j and normalize by $65 \sum_j a_j$. Auxiliary reconstruction uses $\hat{\mathbf{Y}}_j^{\text{RTC}} = \mathbf{X}_{\tau,j} - \tau_j \mathbf{v}_{\theta,j}$ with the same terms as Eq. (5). Setting $d = 0$ recovers the standard objective.

2) *Closed-Loop RL with a Frozen Tracker:* We execute RTC-generated chunks through the frozen perceptive tracker and update only the planner. Following ReinFlow [28], a learned noise scale makes the discretized reverse-flow transitions Gaussian and hence tractable for PPO. Transitions within a chunk share its planner-level advantage, and RTC remains active during rollouts.

At the 50 Hz tracker rate, one reward is shared across all

scenes and behaviors:

$$\begin{aligned}
r_t &= \Delta t \left(r_t^{\text{goal}} + r_t^{\text{loco}} - c_t^{\text{obs}} \right), \quad \Delta t = 0.02 \text{ s}, \\
r_t^{\text{goal}} &= 0.75r_t^{\text{head}} + 2r_t^{\text{prog}} + 4r_t^{\text{arr}} \\
&\quad + 0.5r_t^{\text{speed}} + r_t^{\text{hold}} + 0.1r_t^{\text{alive}}, \\
r_t^{\text{loco}} &= 0.4r_t^{\text{gait}} - 0.005c_t^{\text{act}} - 0.2c_t^{\text{slip}} - 2c_t^{\text{flight}}, \\
c_t^{\text{obs}} &= 4c_t^{\text{contact}} + c_t^{\text{dist}}.
\end{aligned} \tag{7}$$

These terms encode goal reaching and stable stopping, feasible support transitions, and collision avoidance; c_t^{dist} provides dense pre-contact supervision from the clearances between selected hand and foot points and the environment. During RL, arrival requires remaining within 0.35 m of the destination below 0.3 m/s for 0.2 s.

Each chunk controls up to $C = 8$ tracker steps, so rewards and advantages are computed at planner boundaries. For decision j spanning $n_j \leq C$ steps, $\bar{r}_j = \sum_{i=0}^{n_j-1} \gamma_c^i r_{t_j+i}$ and

$$\begin{aligned}
\delta_j &= \bar{r}_j + \gamma_c^{n_j} (1 - m_j^{\text{term}}) V_{j+1} - V_j, \\
A_j &= \delta_j + \gamma_c^{n_j} \lambda_{\text{GAE}} (1 - m_j^{\text{term}}) (1 - m_j^{\text{trunc}}) A_{j+1}.
\end{aligned} \tag{8}$$

Here m_j^{term} and m_j^{trunc} denote true termination and time-limit or rollout truncation, respectively. We use $\gamma_c = 0.98$ and $\lambda_{\text{GAE}} = 0.95$; true terminals suppress bootstrapping, whereas truncations retain the next-state bootstrap but stop advantage recursion. Advantages are batch-normalized.

We train for 1,000 iterations in 128 parallel environments spanning 16 scenes and 1,720 clips. Freezing the tracker exposes the planner to execution-induced deviations without changing the planner-tracker interface.

D. Egocentric Perception and Onboard Deployment

The complete stack runs onboard a Unitree G1 equipped with a Jetson AGX Orin and a Manifold Tech Odin module, without a prebuilt map or offboard computation. Registered point clouds and odometry are fused online into a robocentric 3D occupancy grid maintained by ROG-Map [29]. We extract the same torso-centered three-layer elevation map used in training: each vertical voxel column yields the highest occupied surface, an obstacle underside supported by observed free space beneath it, and the supporting surface below that clearance. Together, the three layers encode supporting geometry, lateral blockage, and overhead clearance; unknown voxels are never treated as free. Fig. 4 contrasts this representation in simulation and onboard operation.

The extracted surfaces are cached and resampled in the torso frame at 20 Hz using the latest odometry, reducing pose staleness between point-cloud updates. The planner runs in a dedicated process with TensorRT FP16 at 6.25 Hz, the tracker runs on the onboard CPU at 50 Hz, and joint targets are published to the robot at 500 Hz.

IV. EXPERIMENTS

Our experiments evaluate two central claims: (i) PASSAGE can autonomously select, compose, and execute

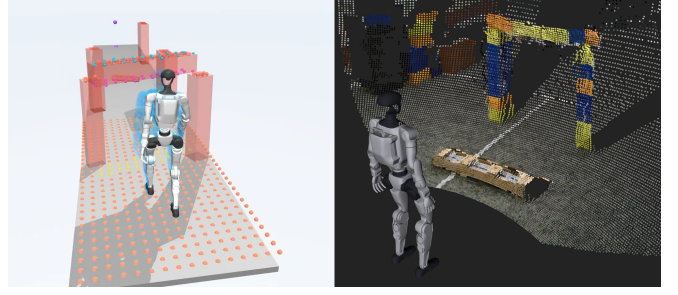


Fig. 4: The shared three-layer geometric representation in simulation (left) and reconstructed online from onboard LiDAR without a prebuilt map (right).

whole-body traversal behaviors across ground-level, lateral, and overhead constraints using a single destination-conditioned planner and a perceptive general tracker, without skill labels or behavior-specific controllers; and (ii) increasing scene-aligned training data yields a robust positive empirical trend in closed-loop generalization to held-out scenes. We further isolate the effects of RTC and closed-loop planner post-training and quantify the complete system under fully onboard real-world execution.

A. Evaluation Protocol

All simulation experiments run in MuJoCo [30] on held-out instances from the procedural generator in Sec. III-A. The test set contains 150 scenes, with 50 at each of three difficulty levels. For every method or configuration, we conduct five rollouts per scene using identical scenes, start-destination pairs, and rollout seeds, yielding 750 episodes. Each episode runs at 50 Hz for at most 60 s. Success (Succ.) requires reaching within 0.5 m of the destination before a fall or timeout; contact-free success (CF-Succ.) additionally requires zero robot-obstacle contact. Fall is the fraction of episodes terminated by low root height or excessive body tilt. Contact/Path is obstacle-contact duration divided by planar distance traveled, in s/m. Foot Slip is the temporal mean of $\sum_{i \in \mathcal{C}_t} \|\mathbf{v}_{i,t}^{xy}\|_2^2$, in m^2/s^2 . Metrics are first averaged within each scene and then macro-averaged across scenes.

B. Overall Closed-Loop Performance

We compare PASSAGE with two complementary baselines under the common evaluation protocol. The released CAT generalist [1] is evaluated without retraining and retains its native interfaces. Although the test scenes are unseen by both systems, they follow PASSAGE’s training distribution and are encountered by CAT zero-shot; this is therefore a system-level transfer comparison.

We also implement a Zhang et al.-style diffusion-tracking pipeline [3]. Its planner uses the same unaugmented, nested 12 h subset and three-layer geometric representation as the corresponding PASSAGE planner. Following the reported design, it predicts 25 frames from two history frames with two denoising steps. A task-specific perceptive tracker is trained on the same subset and subsequently fine-tuned in closed loop with the planner frozen. We follow reported settings

TABLE I: Quantitative comparison, data scaling, and ablations on held-out cluttered scenes. Scaling rows report mean $\pm$ standard deviation over three independent training seeds; all other rows report single checkpoints.

Method	Succ. $\uparrow$	CF-Succ. $\uparrow$	Fall $\downarrow$	Contact/Path $\downarrow$	FSlip $\downarrow$
CAT (released, zero-shot) [1]	0.7027	0.1400	0.2013	0.3192	0.1738
Zhang et al.-style pipeline (our impl., 12 h) [3]	0.8600	0.1920	0.0080	0.5680	0.0120
Ours w/o RTC	0.9267	0.2453	0.0307	0.4038	0.0119
Ours w/o RL post-training	0.9440	0.2640	0.0293	0.1985	0.0185
Ours w/o tracker perception	0.8440	0.1840	0.0693	0.2520	0.0147
Ours w/o PF loss	0.8480	0.2013	0.0253	0.1538	0.0134
Ours, 6 h	0.843 ± 0.004	0.481 ± 0.007	0.008 ± 0.012	0.357 ± 0.051	0.0124 ± 0.0005
Ours, 12 h	0.900 ± 0.005	0.486 ± 0.003	0.016 ± 0.001	0.123 ± 0.018	0.0125 ± 0.0006
Ours, 24 h	0.923 ± 0.003	0.578 ± 0.005	0.011 ± 0.003	0.080 ± 0.003	0.0112 ± 0.0010
Ours, 48 h	0.934 ± 0.007	0.643 ± 0.004	0.010 ± 0.005	0.060 ± 0.001	0.0115 ± 0.0006
Ours, 100 h (w/o aug.)	0.964 ± 0.007	0.689 ± 0.004	0.006 ± 0.002	0.050 ± 0.001	0.0108 ± 0.0021
Ours, 100 h + aug. (final)	0.9867	0.7027	0.0093	0.0422	0.0113

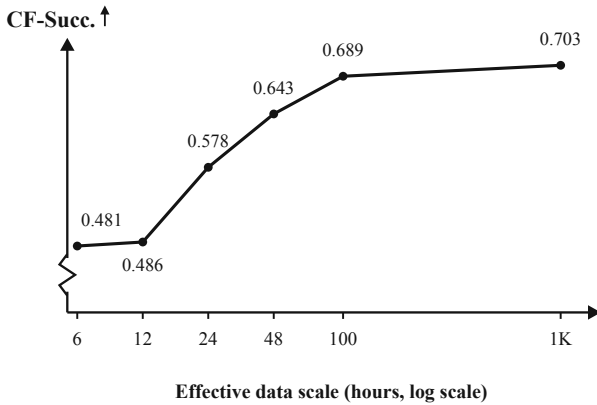


Fig. 5: Closed-loop CF-Succ. across scene-aligned training-data scales. Points from 6 to 100 h are means over three independent training seeds using nested unaugmented subsets; the 1,000 h point is the single final checkpoint obtained through 1:10 scene augmentation of the 100 h corpus.

where available and document our choices for unspecified details. Simulator scene-loading constraints preclude training this tracker as a general tracker.

Final PASSAGE achieves 98.7% Succ. and 70.3% CF-Succ., compared with 70.3% and 14.0% for CAT. The Zhang et al.-style pipeline achieves 86.0% Succ. and 19.2% CF-Succ., whereas PASSAGE at the same 12 h planner-data scale averages 90.0% and 48.6% over three training seeds, respectively, and reduces Contact/Path from 0.5680 to 0.1230 s/m. Thus, both pipelines frequently reach the destination, but PASSAGE completes substantially more trials without contact. Because their tracker training and closed-loop refinement also differ, this comparison evaluates complete pipelines rather than isolating flow matching from diffusion.

C. Scaling Scene-Aligned Training Data

We examine captured-data scaling separately from scene augmentation. At each of 6, 12, 24, 48, and 100 h, we train three planners with independent seeds and report mean

$\pm$ standard deviation. All runs use the same architecture, optimization budget, RTC and PF objectives, closed-loop RL post-training, frozen tracker, and evaluation episodes; across scales, only the planner pre-training subset changes. The final augmented model additionally applies 1:10 scene augmentation to the full 100 h corpus, producing approximately 1,000 h of effective motion-scene pair duration without additional human capture.

Across three seeds, mean Succ. increases from $(84.3 \pm 0.4)\%$ at 6 h to $(96.4 \pm 0.7)\%$ at 100 h, while mean CF-Succ. rises from $(48.1 \pm 0.7)\%$ to $(68.9 \pm 0.4)\%$. Contact/Path decreases from 0.3565 ± 0.0512 to 0.0499 ± 0.0013 s/m. The 6–12 h CF-Succ. change lies within seed variation, whereas Succ. and Contact/Path improve monotonically for every seed. Fall and Foot Slip show no consistent monotonic trend; the strongest gains therefore occur in goal reaching and collision avoidance.

Relative to the three-seed mean of the 100 h no-augmentation control, the single augmented model reaches 98.7% Succ. and 70.3% CF-Succ., with 0.0422 s/m Contact/Path. These are observed differences of 2.2 and 1.3 percentage points in Succ. and CF-Succ., respectively, and a 15.4% reduction in contact exposure. Thus, the 6–100 h study supports a robust positive empirical trend with captured-data scale. We analyze the smaller augmentation gain separately because it reuses the same 100 h of captured motion (Fig. 5). The subsets are nested at the trajectory level, and all test-scene seeds are disjoint from those used for pre-training, scene augmentation, RL post-training, and model selection.

D. Component Ablations

Table I isolates the contributions of RTC, closed-loop reinforcement learning (RL) post-training, tracker-side perception augmentation, and potential-field (PF) regularization. All variants retain the full planner training dataset and change only the indicated component relative to the final system. For planner-side ablations, the component is removed from every stage in which it is used. For the tracker ablation, we replace the perception-enhanced tracker with the base

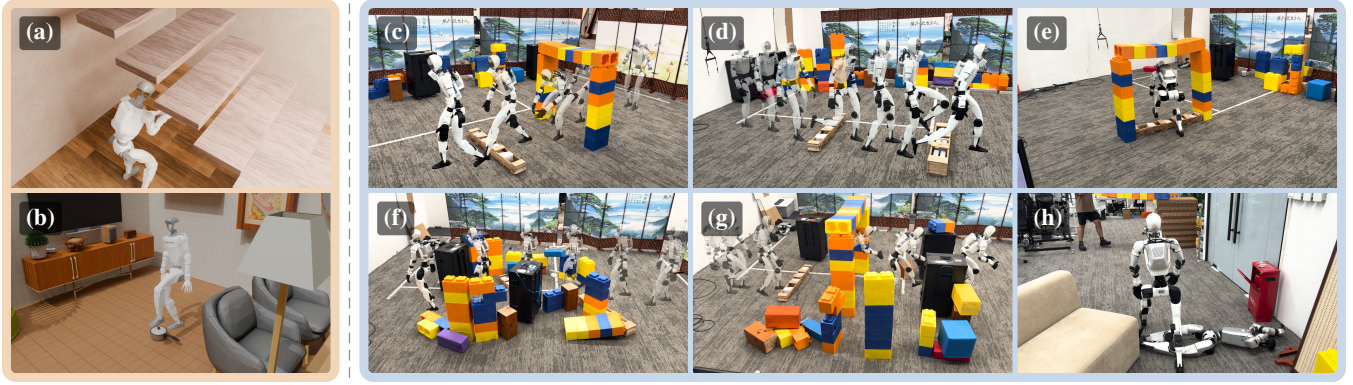


Fig. 6: Qualitative simulated (a)–(b) and real-world (c)–(h) rollouts: (a) duck-under; (b) step-over; (c) step-over followed by duck-under; (d) repeated step-over; (e) concurrent step-over and duck-under; (f) squeeze-through; (g) dense-clutter weaving; and (h) stepping over a fallen robot. Real-world trials use egocentric perception and fully onboard computation; overlays show successive poses.

ScaleBFM checkpoint while leaving the planner and planner-tracker interface unchanged.

Real-time chunking. Removing RTC reduces Succ. from 98.7% to 92.7% and CF-Succ. from 70.3% to 24.5%, while increasing Contact/Path nearly tenfold from 0.0422 to 0.4038 s/m. This safety degradation is consistent with RTC reducing geometry-relative discontinuities across replans, which can otherwise turn small reference shifts into obstacle contact.

Closed-loop planner post-training. Removing RL post-training reduces Succ. to 94.4% and CF-Succ. to 26.4%, while increasing Contact/Path to 0.1985 s/m and Foot Slip to 0.0185. These changes indicate that optimizing the planner through rollouts under the frozen tracker improves realized goal reaching, collision avoidance, and execution quality. The improvement is consistent with reducing the mismatch between offline planner outputs and tracker-realized states without altering the modular planner-tracker interface.

Tracker-side perception augmentation. Replacing the perception-enhanced tracker with the base ScaleBFM tracker reduces Succ. from 98.7% to 84.4% and CF-Succ. from 70.3% to 18.4%, while increasing Fall from 0.9% to 6.9%. Because the planner and planner-tracker interface remain unchanged, this comparison measures the net contribution of tracker-side perception augmentation. The degradation is consistent with local geometric feedback helping correct tracking errors under tight clearances.

Potential-field regularization. Removing the PF loss reduces Succ. to 84.8% and CF-Succ. to 20.1%, while increasing Contact/Path from 0.0422 to 0.1538 s/m. This safety degradation is consistent with PF acting as a geometric prior that discourages residual scene-motion interpenetration introduced by motion capture, retargeting, and scene augmentation.

Together with the preceding scaling study, these results support a complementary division of roles: scene-aligned demonstrations provide the geometry-conditioned behavioral repertoire; PF supplies an explicit collision-avoidance prior;

TABLE II: Real-world traversal with the complete onboard system. Each scenario contains ten distinct physical layouts, each attempted once; all attempts are included in N . Succ. denotes reaching the designated finish region beyond the obstacle layout without a fall or safety intervention. CF-Succ. additionally requires no robot-obstacle contact, as manually annotated by human observers.

Scenario	N	Succ.	CF-Succ.
Step-over	10	10/10	10/10
Duck-under	10	10/10	9/10
Squeeze-through	10	10/10	9/10
Concurrent over-under	10	10/10	9/10
Sequential mixed	10	10/10	8/10
Overall	50	50/50	45/50

RTC promotes consistency across successive plans; closed-loop RL adapts the planner to tracker-realized motion; and tracker-side perception augmentation equips the execution layer with local geometric correction. All component ablations are conducted in simulation, while the following experiments evaluate the resulting complete stack on hardware.

E. Onboard Real-World Evaluation

We evaluate the same planner-tracker pair across 50 physical layouts using destination-only commands, without behavior labels or an explicit skill selector. Table II summarizes the results.

PASSAGE reaches the finish region without a fall or safety intervention in all 50 trials, with 45/50 (90%) contact-free executions. It completes all 20 concurrent and sequential layouts, of which 17 are contact-free, including 8/10 sequential mixed courses. Using a distinct physical layout in every trial extends the evaluation across 50 geometric configurations. Together with the geometry-conditioned behaviors in Fig. 6, these results provide task-level evidence that a single onboard system can select and compose whole-body traversal behaviors without an explicit skill selector. The five contact-bearing completions indicate that collision avoidance, rather

than course completion, remains the principal limitation in the tested layouts.

V. CONCLUSION

We presented PASSAGE, a scalable, perception-conditioned framework for destination-directed humanoid traversal in cluttered environments. Our VR and inertial motion-capture pipeline enabled the collection of 100 h of scene-aligned human demonstrations, expanded through validated scene augmentation to approximately 1,000 h of motion-scene training pairs. From these data, a single flow-matching planner learns to select and compose whole-body behaviors across ground-level, lateral, and overhead constraints, while a perceptive general tracker executes them without skill labels or behavior-specific controllers. RTC promotes consistency across replanning steps, and planner-side RL post-training with a frozen tracker improves closed-loop performance. Across three independent training seeds, scaling captured data from 6 to 100 h increases mean goal-reaching success from 84.3% to 96.4% and contact-free success from 48.1% to 68.9%, while reducing Contact/Path from 0.3565 to 0.0499 s/m. With egocentric perception and fully onboard computation, PASSAGE reaches the destination in all 50 real-world trials, of which 45 are contact-free.

Future work will broaden both the behavioral and perceptual scope of humanoid traversal. More diverse demonstrations could extend the learned repertoire to ascending and descending stairs, climbing onto platforms, and vaulting over obstacles. Complementing geometric sensing with RGB observations may improve perception of transparent surfaces, thin cables, and other structures that remain challenging for LiDAR alone. True to its name, PASSAGE represents one step toward humanoids that traverse human environments with increasingly broad, human-like adaptability.

REFERENCES

- [1] H. Xue, S. Liang, Z. Zhang, Z. Zeng, Y. Liu, Y. Lian, J. Wang, Q. Liu, X. Shi, and L. Yi, "Collision-free humanoid traversal in cluttered indoor scenes," 2026. [Online]. Available: <https://arxiv.org/abs/2601.16035>
- [2] Z. Wu, X. Huang, L. Yang, Y. Zhang, X. Chen, P. Abbeel, R. Duan, A. Kanazawa, C. Sferazza, G. Shi, and C. K. Liu, "Perceptive humanoid parkour: Chaining dynamic human skills via motion matching," 2026. [Online]. Available: <https://arxiv.org/abs/2602.15827>
- [3] Z. Zhang, K. Wen, M. Xu, J. He, C. Li, T. Miki, C. Schwarke, C. Zhang, X. B. Peng, and M. Hutter, "Learning whole-body humanoid locomotion via motion generation and motion tracking," 2026. [Online]. Available: <https://arxiv.org/abs/2604.17335>
- [4] B. Wang, Y. Lu, L. Wang, L. Yu, and X. Xiao, "Moving through clutter: Scaling data collection and benchmarking for 3d scene-aware humanoid locomotion via virtual reality," *arXiv preprint arXiv:2603.05993*, 2026.
- [5] W. Zeng, K. Yin, X. Niu, S. Lu, W. Zhong, J. Chen, F. Jia, X. Chen, Z. Wang, F. Xu, *et al.*, "Scaling behavior foundation model for humanoid robots," *arXiv preprint arXiv:2607.15163*, 2026.
- [6] X. B. Peng, P. Abbeel, S. Levine, and M. van de Panne, "Deepmimic: Example-guided deep reinforcement learning of physics-based character skills," *ACM Trans. Graph.*, vol. 37, no. 4, pp. 143:1–143:14, July 2018. [Online]. Available: <http://doi.acm.org/10.1145/3197517.3201311>
- [7] Z. Chen, M. Ji, X. Cheng, X. Peng, X. B. Peng, and X. Wang, "Gmt: General motion tracking for humanoid whole-body control," 2025. [Online]. Available: <https://arxiv.org/abs/2506.14770>
- [8] Z. Luo, Y. Yuan, T. Wang, C. Li, S. Chen, F. Castañeda, Z.-A. Cao, J. Li, D. Minor, Q. Ben, X. Da, R. Ding, C. Hogg, L. Song, E. Lim, E. Jeong, T. He, H. Xue, W. Xiao, Z. Wang, S. Yuen, J. Kautz, Y. Chang, U. Iqbal, L. J. Fan, and Y. Zhu, "Sonic: Supersizing motion tracking for natural humanoid whole-body control," 2025. [Online]. Available: <https://arxiv.org/abs/2511.07820>
- [9] S. Zhao, Y. Ze, Y. Wang, C. K. Liu, P. Abbeel, G. Shi, and R. Duan, "Resmimic: From general motion tracking to humanoid whole-body loco-manipulation via residual learning," 2025. [Online]. Available: <https://arxiv.org/abs/2510.05070>
- [10] M. Ji, X. Peng, F. Liu, J. Li, G. Yang, X. Cheng, and X. Wang, "Exbody2: Advanced expressive humanoid whole-body control," 2024. [Online]. Available: <https://arxiv.org/abs/2412.13196>
- [11] Z. Zhang, J. Guo, C. Chen, J. Wang, C. Lin, Y. Lian, H. Xue, Z. Wang, M. Liu, J. Lyu, H. Liu, H. Wang, and L. Yi, "Track any motions under any disturbances," 2025. [Online]. Available: <https://arxiv.org/abs/2509.13833>
- [12] P. Li, H. Li, Y. Ma, L. Chang, X. Yang, R. Yu, S. Liao, Y. Zhang, Y. Cao, Q. Zhu, *et al.*, "Kivi: Kinesthetic-visuospatial integration for dynamic and safe egocentric legged locomotion," *arXiv preprint arXiv:2509.23650*, 2025.
- [13] P. Li, H. Li, M. Fan, F. Xu, S. Liao, Y. Ma, Z. Zeng, Z. Wang, Y. Jin, Y. Cao, *et al.*, "Taga: Terrain-aware active gaze learning for generalizable agile humanoid locomotion," *arXiv preprint arXiv:2606.05880*, 2026.
- [14] Z. Wang, Y. Li, T. Ma, Q. Zhang, Y. Fan, H. Xu, S. Yang, and J. Liang, "Perceptive behavior foundation model: Adapting human motion priors to robot-centric terrain," *arXiv preprint arXiv:2606.08059*, 2026.
- [15] Q. Ben, B. Xu, K. Li, F. Jia, W. Zhang, J. Wang, J. Wang, D. Lin, and J. Pang, "Gallant: Voxel grid-based humanoid locomotion and local-navigation across 3d constrained terrains," 2025. [Online]. Available: <https://arxiv.org/abs/2511.14625>
- [16] H. Chen, Z. Li, H. Wang, J. Hu, Z. Li, P. Liu, Q. Zhao, X. Liu, L. Pan, X. Lyu, *et al.*, "Light-loco-parkour: Versatile perceptive whole-body locomotion via multi-skill distillation," *arXiv preprint arXiv:2608.02653*, 2026.
- [17] A. Allshire, H. Choi, J. Zhang, D. McAllister, A. Zhang, C. M. Kim, T. Darrell, P. Abbeel, J. Malik, and A. Kanazawa, "Visual imitation enables contextual humanoid control," *arXiv preprint arXiv:2505.03729*, 2025.
- [18] A. Brandes, H. C. G. Sajelian, M. Patel, D. Hollidt, C. Li, M. Heyrman, O. Hausdoerfer, M. Kaufmann, X. Wang, J. Frey, *et al.*, "Egoht: Egocentric 4d demonstrations of human terrain traversal," *arXiv preprint arXiv:2607.13472*, 2026.
- [19] Q. Liao, T. E. Truong, X. Huang, Y. Gao, G. Tevet, K. Sreenath, and C. K. Liu, "Beyondmimic: From motion tracking to versatile humanoid control via guided diffusion," *Science Robotics*, vol. 11, no. 117, p. eadx8924, 2026.
- [20] J. Yue, Z. Wang, Y. Wang, W. Zeng, J. Wang, X. Xu, Y. Zhang, S. Zheng, Z. Ding, and Z. Lu, "RI from physical feedback: Aligning large motion models with humanoid control," *arXiv preprint arXiv:2506.12769*, 2025.
- [21] Z. Ling, X. Yu, R. Yan, J. Cheng, Z. Wang, Q. Shuai, and C. Zou, "Gentrack: Physical alignment for robot-native motion generation and zero-shot humanoid tracking," *arXiv preprint arXiv:2608.01410*, 2026.
- [22] L. Yang, X. Huang, Z. Wu, A. Kanazawa, P. Abbeel, C. Sferazza, C. K. Liu, R. Duan, and G. Shi, "Omniretarget: Interaction-preserving data generation for humanoid whole-body loco-manipulation and scene interaction," 2025. [Online]. Available: <https://arxiv.org/abs/2509.26633>
- [23] J. P. Araujo, Y. Ze, P. Xu, J. Wu, and C. K. Liu, "Retargeting matters: General motion retargeting for humanoid motion tracking," 2025.
- [24] T. Wang, O. Dionne, M. D. Ruyter, D. Minor, D. Remppe, K. Zhao, M. Petrovich, Y. Yuan, C. Li, Z. Luo, B. Robison, X. Blackwell, B. Antoniazzi, X. B. Peng, Y. Zhu, and S. Yuen, "Motionbricks: Scalable real-time motions with modular latent generative model and smart primitives," 2026. [Online]. Available: <https://arxiv.org/abs/2604.24833>
- [25] M. Xu, Y. Shi, K. Yin, and X. B. Peng, "Parc: Physics-based augmentation with reinforcement learning for character controllers," in *Proceedings of the Special Interest Group on Computer Graphics and Interactive Techniques Conference Conference Papers*, 2025, pp. 1–11.
- [26] D. Liu, Z. Zheng, Y. Sun, L. Zhang, Y. Liu, and H. Wan, "Action-

- prior denoising for smooth real-time chunking,” *arXiv preprint arXiv:2605.25537*, 2026.
- [27] K. Black, A. Z. Ren, M. Equi, and S. Levine, “Training-time action conditioning for efficient real-time chunking,” *arXiv preprint arXiv:2512.05964*, 2025.
- [28] T. Zhang, C. Yu, S. Su, and Y. Wang, “Reinflow: Fine-tuning flow matching policy with online reinforcement learning,” 2025. [Online]. Available: <https://arxiv.org/abs/2505.22094>
- [29] Y. Ren, Y. Cai, F. Zhu, S. Liang, and F. Zhang, “ROG-Map: An efficient robocentric occupancy grid map for large-scene and high-resolution LiDAR-based motion planning,” in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2024, pp. 8119–8125. [Online]. Available: <https://doi.org/10.1109/IROS58592.2024.10802303>
- [30] E. Todorov, T. Erez, and Y. Tassa, “Mujoco: A physics engine for model-based control,” in *2012 IEEE/RSJ international conference on intelligent robots and systems*. IEEE, 2012, pp. 5026–5033.

APPENDIX I

PLANNER ARCHITECTURE, TRAINING, AND REFINEMENT DETAILS

A. Architecture and Conditioning

The 65-D state follows Eq. (1). Root velocities are expressed in the yaw-aligned navigation frame obtained from the pelvis frame by removing roll and pitch at each sample; absolute horizontal position and yaw are omitted. The robot-centric destination $\mathbf{c}_g$ is expressed in the current torso-yaw frame and embedded by an MLP. History and future motion use separate channel-wise statistics computed from the training split, with standard deviations lower-bounded by 10^{-3} . The planner receives the same torso-centered, yaw-aligned three-layer map $\mathbf{E} \in \mathbb{R}^{3 \times 31 \times 61}$ used by the tracker. It follows the torso-relative downward-depth convention in Appendix III and is standardized with training-set statistics before tokenization. Table III summarizes the planner architecture.

We adopt the 16-block, width-1024 scale of the MotionBricks pose backbone [24], but use eight attention heads and directly predict a continuous 25×65 vector field. We do not use MotionBricks’ discrete codebook or root–pose latent decomposition. The terrain, destination, history, and noisy-motion tokenization is inspired by PARC [25], and RTC follows Soft RTC [26].

B. Offline Training and Flow Inference

We sample $u \sim \mathcal{U}(0, 1)$, set $t = \text{clip}(u, 10^{-5}, 1 - 10^{-5})$, and draw $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. Gaussian noise with standard deviation 0.01 is added to normalized history and terrain inputs; the complete history is masked with probability 0.15, and left–right mirroring is applied with probability 0.5. All Smooth- L_1 terms use transition parameter $\beta = 1$. After standard offline pre-training, we fine-tune the same planner with the main-text RTC objective. During this RTC fine-tuning stage, fully committed tokens are excluded from reconstruction and kinematic losses, whereas the potential-field loss is evaluated on all predicted frames.

The root and joint-velocity losses act on the first seven and final 29 state channels, respectively. After unnormalization, the finite-difference loss matches predicted joint velocity to $(\mathbf{q}_i - \mathbf{q}_{i-1})/\Delta t$, where $\Delta t = 0.02$ s. Foot sliding is penalized when consecutive ankle positions lie within a soft 0.08 m

support band. Body-keypoint jerk is evaluated at the pelvis, torso, ankles, and wrists with a 750 m/s^3 hinge threshold, and the oriented-box loss applies a 0.20 m margin to the same six points.

For potential-field regularization, the 11 anchors are the pelvis, torso, head, bilateral knees, feet, shoulders, and palms, implemented at the ankle-roll and wrist-yaw links. Let d_{sdf} be signed distance, $\hat{\mathbf{G}}$ the normalized guidance direction, $\Delta \mathbf{p}$ an anchor displacement, and $r_{\text{PF}} = 0.20$ m. We use

$$\begin{aligned} \mathcal{L}_{\text{rep}} &= \left\langle \frac{(r_{\text{PF}} - d_{\text{sdf}})^2}{2r_{\text{PF}}} \right\rangle_{d_{\text{sdf}} < r_{\text{PF}}}, \\ \mathcal{L}_{\text{dir}} &= \left\langle [-\widehat{\Delta \mathbf{p}}^\top \hat{\mathbf{G}}]_+ \text{clip}\left(\frac{\|\Delta \mathbf{p}\|}{0.05 \text{ m}}, 0, 1\right) \right\rangle, \end{aligned} \quad (9)$$

where $[x]_+ = \max(x, 0)$ and $\widehat{\Delta \mathbf{p}} = \Delta \mathbf{p}/(\|\Delta \mathbf{p}\|_2 + 10^{-8} \text{ m})$. The first average is over anchors with $d_{\text{sdf}} < r_{\text{PF}}$ and is set to zero when none are active; the second is over consecutive anchor displacements. We set $\mathcal{L}_{\text{PF}} = \mathcal{L}_{\text{rep}} + \mathcal{L}_{\text{dir}}$. Scene fields are trilinearly interpolated and used only during training.

At inference, generation starts from Gaussian noise and numerically integrates the learned vector field from $t = 1$ to $t = 0$. The planner outputs 25 frames; the first eight are executed before replanning, consistent with 6.25 Hz planning and 50 Hz tracking.

C. Real-Time Chunking and Tracker Interface

At inference, the temporally aligned unexecuted suffix of the preceding chunk supplies the RTC prior under the token-wise blending rule defined in the main text. If no valid suffix exists, including the first plan after reset, we set $d = 0$. The four-frame history is subsequently updated from tracker-executed rather than planned states.

After denormalization, each generated chunk is re-anchored to the latest measured pelvis pose. For successive generated frames and $\Delta t = 0.02$ s, the planar root trajectory is reconstructed as

$$\begin{aligned} \mathbf{p}_{j+1,xy}^w &= \mathbf{p}_{j,xy}^w + \Delta t R_{xy}(\psi_j) \mathbf{v}_{j,xy}^n, \\ \psi_{j+1} &= \psi_j + \Delta t \omega_{j,z}^n, \end{aligned} \quad (10)$$

where $R_{xy}(\psi)$ denotes planar yaw rotation. Predicted root height and gravity recover vertical position and tilt, and forward kinematics produces the 14-link references defined in Appendix II.

D. Planner-Side RL Post-Training

We execute RTC-generated chunks through the frozen perceptive tracker and update only the planner. Following ReinFlow [28], a learned noise scale makes the discretized reverse-flow transitions Gaussian and tractable for PPO. Transitions belonging to one generated chunk share the planner-boundary advantage defined in the main text; the tracker remains frozen throughout.

Let $\Delta \mathbf{g}_t$ be the horizontal pelvis-to-goal displacement, $d_t = \|\Delta \mathbf{g}_t\|_2$, and $\hat{\mathbf{g}}_t = \Delta \mathbf{g}_t/(d_t + 10^{-4} \text{ m})$; we set $\hat{\mathbf{g}}_t = \mathbf{0}$ at the goal. Let $\mathbf{v}_t$ be horizontal pelvis velocity and I a binary

TABLE III: Flow-planner architecture and tokenization.

Component	Configuration
Time / goal	Sinusoidal flow-time embeddings and an MLP goal embedding, projected to 1024-D
Terrain	Three stride-1 3×3 Conv-GN-SiLU layers ($3 \rightarrow 32 \rightarrow 64 \rightarrow 64$; GN groups $4/8/8$), replicate padding to 33×63 , and a 3×3 , stride-3 projection to 1024-D; 231 tokens
Motion	Separate shared two-layer MLPs for four history and 25 noisy-future tokens
Sequence	Terrain, history, and future tokens use separate fixed positional encodings and learned modality embeddings
Transformer	16 pre-norm blocks, width 1024, eight heads, FFN width 4096, GELU, dropout 0.1, and global bidirectional attention
Output	LayerNorm followed by a $1024 \rightarrow 1024 \rightarrow 65$ head on the final 25 tokens

indicator. Table IV defines the reward atoms whose weights are given in the main text. Physical quantities are evaluated numerically in SI units; the scalar reward coefficients absorb the corresponding units.

For c^{dist} , columns less than 0.06 m above nominal ground are ignored. We use toe, sole, and heel points on both feet and one endpoint on each hand. For endpoint k and retained vertical column j ,

$$c_{kj} = [\|\mathbf{p}_k - \Pi_j(\mathbf{p}_k)\|_2 - r_k - r_{\text{cell}}]_+, \quad (11)$$

$$c^{\text{dist}} = \max_{k,j} \mathbf{1}[c_{kj} < 0.10 \text{ m}] \exp[-c_{kj}/(0.02 \text{ m})],$$

where Π_j projects onto column j , $r_{\text{cell}} = 0.0354 \text{ m}$, and r_k is 0.012 m for foot points and 0.035 m for hand points. Foot longitudinal offsets are $\{0.125, 0.040, -0.045\} \text{ m}$ with vertical offset -0.029 m ; hand offsets are $(0.15, \mp 0.02, 0) \text{ m}$. All offsets are expressed in their corresponding link-local frames. Taking the maximum prevents an unsafe endpoint from being diluted by safe ones.

Planner-side RL post-training runs for 1,000 iterations in 128 parallel environments spanning 16 training scenes and 1,720 motion clips. We use $\gamma_c = 0.98$ and $\lambda_{\text{GAE}} = 0.95$, and batch-normalize the advantages, as described in the main text.

APPENDIX II

PERCEPTION-ENHANCED SCALEBFM DETAILS

We use the medium ScaleBFM-compatible Humanoid Transformer architecture [5], initialized from our checkpoint pretrained for 20,000 iterations on a separate 1,000 h Noitom general-motion corpus for the backpack-equipped 29-DoF G1 described in the main text. This corpus is distinct from PASSAGE’s scene-aligned planner-training corpus. Perceptive adaptation uses only our scene-aligned traversal references and no planner-generated rollouts. The actor has four Transformer blocks, width 256, four attention heads, and a 256-dimensional SwiGLU feed-forward layer. PASSAGE adds independently parameterized terrain encoders to

the actor and critic; the deployed actor contains 3.075 M parameters.

A. Tracker Interface and Terrain Conditioning

The policy runs at 50 Hz. Let B denote the current pelvis frame. Each actor proprioceptive frame contains projected gravity, pelvis angular velocity, joint displacement from the nominal pose, and joint velocity:

$$\mathbf{s}_t^p = [\mathbf{g}_t^B, \boldsymbol{\omega}_t^B, \mathbf{q}_t - \mathbf{q}^{\text{nom}}, 0.05\dot{\mathbf{q}}_t] \in \mathbb{R}^{64}. \quad (12)$$

Let $z_t^p = f_p(\mathbf{s}_t^p)$ and $z_t^a = f_a(\mathbf{a}_t)$ denote the 256-D outputs of the learned proprioception and action tokenizers. The three-frame proprioceptive-action history comprises three proprioceptive frames and the two intervening actions, tokenized as $[z_{t-2}^p, z_{t-2}^a, z_{t-1}^p, z_{t-1}^a, z_t^p, e]$, where e is the learned action-query token.

Let $(\mathbf{p}_i, \mathbf{R}_i)$ and $(\mathbf{p}_{i,t+\delta}^*, \mathbf{R}_{i,t+\delta}^*)$ denote the current and reference poses of link i , respectively, where δ is measured in 50 Hz control frames. Define $\mathcal{R}_6(\mathbf{R}) = [(\mathbf{R}\mathbf{e}_x)^\top, (\mathbf{R}\mathbf{e}_z)^\top]^\top \in \mathbb{R}^6$. For each future offset δ , the actor reference is

$$\mathbf{x}_{t,\delta}^{\text{ref}} = \left[\left\{ \begin{array}{c} \mathbf{R}_B^\top(\mathbf{p}_{i,t+\delta}^* - \mathbf{p}_B) \\ \mathbf{R}_B^\top(\mathbf{p}_{i,t+\delta}^* - \mathbf{p}_i) \\ \mathcal{R}_6(\mathbf{R}_B^\top \mathbf{R}_{i,t+\delta}^*) \\ \mathcal{R}_6(\mathbf{R}_i^\top \mathbf{R}_{i,t+\delta}^*) \end{array} \right\}_{i \in \mathcal{B}}, \delta, \mathbf{m} \right], \quad (13)$$

where $|\mathcal{B}| = 14$ and $\mathbf{m} = \mathbf{1}_{14}$ is the whole-body mask. The four link-wise blocks contain 252 components; appending δ and the mask yields a 267-D actor token. The actor receives no reference velocities. The critic omits the mask and appends link linear- and angular-velocity errors, giving $253 + 14(3 + 3) = 337$ components per reference frame. The links are the pelvis; bilateral hip-roll, knee, and ankle-roll links; torso; and bilateral shoulder-roll, elbow, and wrist-yaw links.

During perceptive adaptation, actor offsets are $\{0, 1, 2, 3, 4, \delta_{\text{far}}\}$, with $\delta_{\text{far}} \sim \mathcal{U}\{5, \dots, 32\}$ sampled once per episode. Closed-loop PASSAGE instead uses $\{0, 1, 2, 3, 4, 5\}$, while the critic uses $\{0, 1, 2, 4, 8, 16, 32\}$. Out-of-range indices are clamped at clip boundaries. Because the planner supplies 25 frames every eight control steps, no padding is required during normal execution.

The current elevation map $\mathbf{E}_t \in \mathbb{R}^{3 \times 31 \times 61}$ is expressed in the same torso-centered, yaw-aligned coordinate frame used by the planner, at 0.05 m horizontal resolution. The tracker consumes downward depth clipped to $[-3, 3] \text{ m}$ directly, without a validity mask or the planner-specific normalization described above. During deployment, the most recent map is held between the 20 Hz resampling updates. Map reconstruction and missing-cell handling are detailed in Appendix III. The terrain encoder uses three ELU convolutions with 3×3 kernels, stride 2, padding 1, and channels $3 \rightarrow 24 \rightarrow 48 \rightarrow 96$. Adaptive 2×4 average pooling and a linear $96 \rightarrow 256$ projection produce eight terrain tokens. Tokenizing the six actor reference frames gives $\mathbf{Z}_t^{\text{ref}} \in \mathbb{R}^{6 \times 256}$, and fusion is

$$\mathbf{Z}_t^E = f_E(\mathbf{E}_t) \in \mathbb{R}^{8 \times 256}, \quad \bar{\mathbf{Z}}_t^{\text{ref}} = [\mathbf{Z}_t^{\text{ref}}; \mathbf{Z}_t^E]. \quad (14)$$

TABLE IV: Planner-side RL reward atoms before the main-text weights and common Δt factor.

Term	Definition
r_{head}	$\hat{\mathbf{g}}_t^\top \mathbf{v}_t / (\ \mathbf{v}_t\ + 10^{-4} \text{ m/s})$; zero at rest
r_{prog}	$\text{clip}((d_{t-1} - d_t)/\Delta t, -3 \text{ m/s}, 3 \text{ m/s})$
r_{arr}	Δt^{-1} once the stable-arrival criterion defined in the main text is first satisfied
r_{speed}	$\exp[-(\mathbf{v}_t^\top \hat{\mathbf{g}}_t - v_t^*)^2 / (0.2 \text{ m/s})^2]$, where $v_t^* = \min(0.6 \text{ m/s}, d_t / (1 \text{ s}))$
r_{hold}	$\exp[-d_t^2 / (0.35 \text{ m})^2] \exp[-\ \mathbf{v}_t\ ^2 / (0.3 \text{ m/s})^2]$
r_{alive}	Nonterminal indicator
r_{gait}	$0.6I^{\text{single}} + 0.2I^{\text{double}} + 0.5I^{\text{single}}I[d_t > 0.1 \text{ m}]s^{\text{swing}} + 0.5I^{\text{single-landing}}b$, where s^{swing} is goal-directed swing-foot speed divided by 0.5 m/s and clipped to $[0, 1]$; $b = 0.5/1/0$ for the first, alternating, or repeated-same-foot landing
c_{act}	$\ \mathbf{a}_t - \mathbf{a}_{t-1}\ _2^2$
c_{slip}	$\sum_f I_{f,t}^{\text{contact}} \ \mathbf{v}_{f,t}^{xy}\ _2^2$
c_{flight}	Indicator that neither foot is in contact
c_{contact}	Number of obstacle-contact channels whose maximum force norm within the current control interval exceeds 1 N
c_{dist}	Maximum hand/foot-to-obstacle proximity penalty within 0.10 m

TABLE V: Residual-action scales, low-level gains, and torque limits.

Joint group	s_a (rad)	K_p	K_d	τ_{max} (N m)
Hip pitch/roll; knee	.3507	99.10	6.31	139
Hip yaw; waist yaw	.5476	40.18	2.56	88
Ankle; waist pitch/roll	.3070	28.50	1.81	35
Shoulder; elbow; wrist roll	.4386	14.25	.91	25
Wrist pitch/yaw	.0849	39.48	2.51	13.4

The actor concatenates six reference tokens with the eight terrain tokens, giving 14×256 keys and values for cross-attention. The critic uses seven reference and eight terrain tokens, giving 15×256 . Actor and critic terrain encoders share the architecture but not their parameters.

B. Control and Perceptive Adaptation

The actor predicts a 29-D residual action. During training, actions are sampled from a diagonal Gaussian initialized with standard deviation 0.8; deployment uses the mean. Joint targets and simulated torques are

$$\begin{aligned} \mathbf{q}_t^{\text{des}} &= \mathbf{q}^{\text{nom}} + \mathbf{s}_a \odot \mathbf{a}_t, \\ \boldsymbol{\tau}_t &= \text{clip}(\mathbf{K}_p(\mathbf{q}_t^{\text{cmd}} - \mathbf{q}_t) - \mathbf{K}_d\dot{\mathbf{q}}_t, -\boldsymbol{\tau}_{\text{max}}, \boldsymbol{\tau}_{\text{max}}). \end{aligned} \quad (15)$$

Under joint-encoder-bias randomization, $\mathbf{q}_t^{\text{cmd}} = \mathbf{q}_t^{\text{des}} - \mathbf{b}_q$. Torque saturation remains active. The nominal pose uses hip pitch -0.312 , knee 0.669 , ankle pitch -0.363 , shoulder pitch 0.2 , shoulder roll $+0.2$ (left)/ -0.2 (right), and elbow 0.6 rad, with all other angles zero. Table V reports the joint-group parameters. Each target is held for four 5 ms MuJoCo steps.

Perceptive adaptation is performed in MJLab/MuJoCo using 90 scenes from the easy training split, all disjoint from the 150 held-out evaluation scenes. Each environment samples only references aligned with its assigned scene, and the three-layer maps are ray-cast online from simulator geometry. The tracker therefore sees exact simulated geometry during adaptation; reconstruction error, map latency, and terrain-cell corruption are not simulated. The tracker is trained only with dataset references and never rolls out the planner. It remains a single shared policy across all adaptation scenes and motions.

For the first 200 PPO iterations, only the actor terrain encoder and complete critic are trained; all other actor

modules remain frozen. We then unfreeze the complete actor and continue adaptation for 3,800 iterations. The resulting iteration-4,000 checkpoint is fixed across all PASSAGE configurations except the main-text “w/o tracker perception” ablation. Training is distributed across 32 RTX 4090 GPUs with 2,048 environments and 64-step rollouts. We use Adam with an adaptive-KL schedule, actor and critic learning rates of 10^{-5} and 5×10^{-4} , two update epochs, 16 minibatches per GPU, PPO clip 0.2, desired KL 0.01, $\gamma = 0.99$, $\lambda = 0.95$, entropy coefficient 0.005, value coefficient 1, and gradient clipping at 1.0.

Here, tracker-side perception augmentation denotes the complete two-stage procedure that adds terrain conditioning and adapts the tracker. The ablation restores the base ScaleBFM checkpoint while retaining the same kinematic-reference interface; it is therefore a stage-level ablation rather than an isolation of the terrain tokens alone.

C. Rewards and Randomization

The tracker-adaptation objective below is distinct from the planner-side RL objective in Appendix I-D. Let $k_\sigma(e) = \exp(-e/\sigma^2)$. The tracking reward contains pelvis position and orientation terms with $(w, \sigma) = (0.5, 0.3)$ and $(0.5, 0.4)$; mean non-pelvis link position, orientation, linear-velocity, and angular-velocity terms with $(w, \sigma) = (1, 0.3)$, $(1, 0.4)$, $(1, 1.0)$, and $(1, 3.14)$; and joint-position and joint-velocity terms with $(w, \sigma) = (0.5, 1.25)$ and $(0.25, 12)$, respectively. Position and velocity terms use squared Euclidean errors inside k_σ , and orientation terms use squared geodesic errors. Let $c_f \in \{0, 1\}$ denote contact of foot f ; all sums over f include both feet. Additional rewards are $0.5 \exp(-13 \sum_f |z_f - z_f^*|)$ for foot height, $0.1 \exp(-25 \sum_f c_f (1 - [\mathbf{R}_f]_{zz}))$ for flat-foot contact, and a unit survival reward. The penalties are

$$\begin{aligned} & -0.1\|\mathbf{a}_t - \mathbf{a}_{t-1}\|^2 - 10c_{\text{joint}} - 0.1c_{\text{self}} - 0.1c_{\text{foot}} \\ & -0.75 \sum_f c_f \|\mathbf{v}_{f,xy}\|^2 - 0.005 \sum_{j \in \text{knee}} \left(\frac{[-\tau_j \dot{q}_j - 5]_+}{50} \right)^2 \\ & -0.02 \sum_j (\tau_j / \tau_{j,\text{max}})^2 - c_{\text{trk-contact}}, \end{aligned} \quad (16)$$

where c_{joint} penalizes violations of the inner 90% joint range, c_{self} counts self-contact channels above 10 N, c_{foot} is the mean reference-contact mismatch of the two feet, and $c_{\text{trk-contact}}$ counts robot–obstacle contact channels above 1 N. This force gate is used only by the adaptation reward; system evaluation follows the contact criterion in the main text. The total reward is multiplied by the 0.02-s policy period. There is no terrain-reconstruction or explicit clearance objective; geometric conditioning is learned through tracking, survival, and obstacle-contact returns.

Tracker-adaptation episodes last at most 10 s and terminate when the pelvis-height error exceeds 0.25 m, pelvis-orientation error exceeds 1 rad, ankle or wrist vertical error exceeds 0.25 m, or any reference-link position error exceeds 0.5 m. Obstacle contact alone is not terminal.

At environment construction, we randomize simulated joint-zero offsets by ± 0.01 rad, foot–ground friction in $[0.6, 2.8]$, torso COM by $\pm(0.025, 0.05, 0.05)$ m, hand payload in $[0, 1]$ kg, and joint-encoder bias by ± 0.015 rad. At reset, PD gains are scaled in $[0.9, 1.1]$; root position, root orientation, joint pose, linear velocity, and angular velocity are perturbed within $\pm(0.05, 0.05, 0.01)$ m, $\pm(0.1, 0.1, 0.2)$ rad, ± 0.1 rad, $\pm(0.5, 0.5, 0.2)$ m/s, and $\pm(0.52, 0.52, 0.78)$ rad/s, respectively. Velocity perturbations recur every 1–3 s. Per-step noise is applied to projected gravity (± 0.05), pelvis angular velocity (± 0.2 rad/s), joint position (± 0.01 rad), joint velocity (± 0.5 rad/s before scaling), and reference-pose features (± 0.05).

APPENDIX III

ONBOARD DEPLOYMENT DETAILS

A. Multi-Layer Elevation Map Reconstruction

Registered point clouds and odometry are fused into the robocentric 3D occupancy grid maintained by ROG-Map [29]. From this grid, we construct the same torso-centered, yaw-aligned three-layer elevation map used in training, with 31 lateral and 61 longitudinal samples at 0.05 m horizontal resolution. For horizontal cell (u, v) , let $\mathcal{V}_{uv}(k) \in \{O, F, U\}$, denoting occupied, known-free, and unknown space. With the vertical index increasing upward, for a column containing occupied voxels we define

$$\begin{aligned} k_{uv}^{\text{top}} &= \max\{k \mid \mathcal{V}_{uv}(k) = O\}, \\ \mathcal{K}_{uv}^{\text{mid}} &= \left\{ k \leq k_{uv}^{\text{top}} \mid \begin{array}{l} \mathcal{V}_{uv}(k) = O \\ \mathcal{V}_{uv}(k-1) = F \end{array} \right\}, \\ \mathcal{K}_{uv}^{\text{bot}}(k_m) &= \left\{ k < k_m - 1 \mid \begin{array}{l} \mathcal{V}_{uv}(k) = O \\ \mathcal{V}_{uv}(k+1) = F \end{array} \right\}. \end{aligned} \quad (17)$$

The top index gives the highest occupied surface. If $\mathcal{K}_{uv}^{\text{mid}}$ is nonempty, set $k_{uv}^{\text{mid}} = \max \mathcal{K}_{uv}^{\text{mid}}$ and evaluate $\mathcal{K}_{uv}^{\text{bot}}(k_{uv}^{\text{mid}})$; if the latter is also nonempty, set k_{uv}^{bot} to its maximum. Let $z_+(k)$ and $z_-(k)$ denote the upper and lower faces of voxel k . When $z_-(k_{uv}^{\text{mid}}) - z_+(k_{uv}^{\text{bot}}) \geq 0.05$ m, the overhang is encoded by $z_{uv}^{\text{top}} = z_+(k_{uv}^{\text{top}})$, $z_{uv}^{\text{mid}} = z_-(k_{uv}^{\text{mid}})$, and $z_{uv}^{\text{bot}} = z_+(k_{uv}^{\text{bot}})$. The latter two surfaces are therefore an obstacle underside certified by observed free space beneath it and the supporting surface below that clearance. If either transition is absent or the clearance is smaller, $z_+(k_{uv}^{\text{top}})$ is

repeated across the three channels. Unknown voxels never satisfy a known-free predicate and are therefore never used to certify an underside or clearance. Missing layer values are completed only in the elevation cache; completion neither changes occupancy labels nor certifies unknown space as free.

To suppress sparse-LiDAR artifacts, within a detected-overhang mask and its one-cell dilation we compare each support candidate with the 75th percentile of valid supports in a 5×5 neighborhood. A candidate more than 0.4 m above this reference is replaced when at least four neighbors agree within two vertical voxels. Queried columns without a valid support are completed by iteratively propagating the minimum support height among their eight-connected neighbors; for a column with no occupied surface, the completed support is repeated across the three channels. Both operations modify only the elevation cache, not the underlying occupancy grid.

The resulting world-frame surface heights z_{uv}^ℓ are converted to torso-relative downward depths,

$$E_i^\ell(u, v) = \text{clip}(z_i^{\text{torso}} - z_{uv}^\ell, -3 \text{ m}, 3 \text{ m}). \quad (18)$$

Here, $\ell \in \{\text{top}, \text{mid}, \text{bot}\}$. The tracker consumes these clipped metric depths, whereas the planner applies the normalization in Appendix I-A. Surface extraction is updated with accepted point clouds, and the cached surfaces are resampled in the torso frame at 20 Hz using the latest odometry.

B. Onboard Runtime Details

The complete stack runs onboard a Unitree G1 equipped with a Jetson AGX Orin and a Manifold Tech Odin module, without a prebuilt map or offboard computation. The planner is exported to ONNX and executed in FP16 through the ONNX Runtime TensorRT provider in a dedicated OS process. A new plan is requested every eight 50 Hz control steps, giving the reported 6.25 Hz planning rate. Requests and results are exchanged through a multiprocessing pipe, while the tracker executes on the onboard CPU in the 50 Hz control thread. The latest joint target is transferred through POSIX shared memory to an out-of-process C++ bridge and republished to the robot at 500 Hz.

We provide implementation details for the Zhang et al.-style diffusion-tracking pipeline evaluated in the main text. This is our adaptation rather than an evaluation or reproduction of the authors’ original system. We retain the reported 25-frame horizon, two history frames, two-step online denoising, and closed-loop tracker adaptation with the motion generator frozen. The diffusion planner and a task-specific perceptive tracker are trained from scratch using the same unaugmented, nested 12-h subset. Because of simulator scene-loading constraints, this implementation uses a tracker specialized to that subset rather than a general tracker.

Diffusion planner. For compatibility with our robot and benchmark, the planner uses PASSAGE’s 65-D motion state, 5-D torso-yaw-frame destination, and $3 \times 31 \times 61$ elevation map. Its terrain encoder contains three stride-1 3×3 Conv-GN-SiLU layers ($3 \rightarrow 32 \rightarrow 64 \rightarrow 64$), replicate padding to 33×63 , and a stride-3 projection to 256-D, yielding 231 terrain tokens. The denoiser comprises eight pre-norm Transformer blocks with width 256, eight attention heads, FFN width 1024, GELU, dropout 0.05, and global bidirectional attention. We use discrete VP diffusion with $T = 21$, a squared-cosine schedule ($s = 0.008$), β values clipped to $[10^{-4}, 0.9999]$, and direct clean-motion prediction. The training objective combines clean-motion MSE with velocity and jerk losses weighted by 0.05 and 0.02, respectively; the jerk loss uses a $1,000 \text{ m/s}^3$ hinge threshold.

The planner is trained for 4,000 epochs using AdamW, batch size 64 per rank, learning rate 10^{-4} , $(\beta_1, \beta_2) = (0.9, 0.95)$, $\epsilon = 10^{-8}$, weight decay 10^{-4} , gradient-norm clip 10, and seed 42, without warmup, EMA, or learning-rate scheduling. At inference, deterministic DDIM evaluates the denoiser at $k = 20$ and $k = 0$ with $\eta = 0$. At each step, history-conditioned and history-masked predictions are blended with equal weight, requiring four forward passes per replan. Fresh Gaussian noise is sampled at every replan, and the first eight predicted frames are executed, giving 6.25 Hz

planning under 50 Hz tracking.

Tracker pre-training. Following the dataset-only tracker-training stage of Zhang et al., we train a task-specific perceptive tracker from scratch on the same unaugmented 12-h motion-scene subset. Zhang et al. use an RL-based whole-body reference tracker; the ScaleBFM-compatible backbone used here is our implementation choice for compatibility with our 29-DoF robot and benchmark. It contains four Transformer blocks with width 256, four attention heads, FFN width 256, and a $3 \rightarrow 24 \rightarrow 48 \rightarrow 96$ terrain CNN that produces eight terrain tokens. The policy outputs 29 residual joint-position commands. All model parameters, including the terrain encoder, are randomly initialized. During this stage, the tracker is trained only with dataset references and does not receive planner-generated rollouts.

Tracker pre-training uses separate Adam optimizers with actor and critic learning rates of 10^{-5} and 5×10^{-4} , desired KL 0.01, PPO clip 0.2, $\gamma = 0.99$, $\lambda = 0.95$, entropy coefficient 0.005, two update epochs, 16 minibatches, and gradient-norm clip 1.0. Each iteration collects 64 simulator steps per environment, and training runs for 14,000 iterations.

Closed-loop tracker adaptation. After dataset-only tracker pre-training, the diffusion planner remains frozen in evaluation mode, while the tracker actor, terrain encoder, and critic are optimized using planner-generated references conditioned on executed robot-state history. This is the only stage in which the tracker receives planner-generated rollouts. PPO augments the tracker imitation and regularization rewards with a destination-heading reward and a robot-obstacle contact penalty. Each iteration collects 24 simulator steps per environment using 1,024 environments per rank. Adaptation continues for 20,000 iterations with the same PPO coefficients and learning rates as tracker pre-training, and the final checkpoint is evaluated.

As stated in the main text, differences in tracker architecture, training, and closed-loop refinement mean that this experiment compares complete pipelines rather than isolating flow matching from diffusion.