

Uncertainty-Aware Local Planning for Quadrupeds in Perceptually Degraded Environments

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ABSTRACT

Airborne dust, fog, and low light corrupt the range measurements on which a legged robot's local planner depends, and they tend to do so precisely when reactive collision avoidance matters most. This paper presents an uncertainty-aware local planner for quadrupeds that couples the configuration-driven AgniNav planning backbone with a FutureRay-style predictor of future free range along control-aligned directions. For every candidate command, the predictor outputs a point estimate and an uncertainty envelope that is recalibrated by degradation-stratified conformal prediction. When the control-aligned envelope width exceeds a threshold, the planner widens its safety margin and caps the commanded speed; below the threshold it reproduces the nominal policy exactly, and every modulated quantity is Lipschitz in the excess uncertainty. The planner was evaluated on an ANYmal in Isaac Lab across 15 scenes with sweeps over dust opacity (0 to 80 percent), illuminance (50 to 800 lx), and range dropout (0 to 40 percent), and in a dusty warehouse bay and a dim parking structure. It reached a success rate of 87.9 percent, compared with 76.9 percent for the nominal planner and 82.5 percent for fixed 1.5x margin inflation, while raising mean speed from 1.82 to 1.94 m/s, extending collision-free distance from 3.4 to 3.8 km per collision, and retaining 99.2 percent clean-regime parity. Removing envelope calibration lowered success to 74.0 percent, below the nominal planner. Recorded failure cases, including a 9 s LiDAR dropout, illustrate both the mechanism and its limits.

INDEX TERMS quadruped navigation, local planning, perceptual degradation, uncertainty quantification, conformal prediction, ANYmal

KAGG NOTE Range uncertainty should change a local planner only where it is calibrated and only in excess of what the nominal safety margin already absorbs; below that level, the nominal policy should be left untouched.

01 Introduction

Learned locomotion controllers now allow quadrupeds such as ANYmal to traverse stairs, rubble, and steep natural terrain at speeds that were out of reach a few years ago [1, 2, 3]. Field campaigns in mines, tunnels, and urban underground structures have shown, however, that perception, more often than locomotion, limits what the robot can do in such deployments [4, 5, 6]. Airborne dust and fog attenuate LiDAR returns and inject spurious near-range echoes, low illuminance degrades stereo depth, and transient sensor faults remove entire sectors of the range image [7, 8, 9]. These conditions corrupt exactly the near-field geometry that a local planner needs for reactive collision avoidance, and they tend to arise when the robot is moving through confined, cluttered space.

Two recent lines of work make the local planning problem for legged robots more tractable. AgniNav [10] separates the planning stack from the specific robot by operating on an abstract configuration (a collision envelope, sensor parameters, and velocity limits), so that one planner can be instantiated across embodiments. FutureRay [11] replaces generic obstacle queries with predictions of future free range along the directions that the robot's own candidate commands will actually traverse, aligning perception with what the controller can execute. Neither component, as published, specifies how the planner should behave when the range information itself becomes unreliable. A

planner that consumes point predictions treats a range estimate obtained through dense dust with the same confidence as one obtained in clear air.

The standard engineering response is to inflate safety margins uniformly. Uniform inflation pays a constant price in clear conditions (narrow passages become infeasible and the robot slows or detours) while still offering no protection when the actual range error exceeds the inflated margin. Learned predictive uncertainty [12, 13] offers a more targeted signal, but raw network uncertainties are frequently miscalibrated [14, 15], and a planner that reacts to miscalibrated uncertainty can perform worse than one that ignores it. The gap this paper addresses is therefore a planner that (i) consumes range uncertainty in the same control-aligned coordinates in which it plans, (ii) uses uncertainty that has been calibrated under the degradation conditions it will face, (iii) reacts only to uncertainty in excess of what the nominal margin already absorbs, and (iv) reduces exactly to the nominal planner when the uncertainty is small.

The contributions are as follows.

1. An uncertainty-aware local planner built on the AgniNav configuration interface, in which a FutureRay-style predictor supplies, for every candidate command and future time step, a range estimate together with an uncertainty envelope (Sec. 4).

2. A degradation-stratified conformal recalibration of the predictor’s heteroscedastic output, which yields per-query coverage statements within each degradation stratum (Sec. 4.3).
3. A threshold-gated modulation law that widens safety margins and caps speed in proportion to excess control-aligned uncertainty, with three properties: exact recovery of the nominal policy below threshold in finite time, an envelope-conditional clearance bound, and Lipschitz dependence of all modulated quantities on the excess uncertainty (Sec. 4.7).
4. An evaluation on ANYmal in Isaac Lab across 15 scenes with sweeps of dust opacity, illuminance, and range dropout, and in a dusty warehouse bay and a dim parking structure, including baselines, an ablation, and an analysis of recorded failure cases (Secs. 5–6).

02 Related Work

2.1 Configuration-driven and cross-embodiment local planning

AgniNav [10] is the backbone of this work. It describes a robot through a compact configuration: a four-parameter collision envelope (collision-relevant height, front length, rear length, and half width), sensor placement, and velocity limits. The collision-relevant height conditions the perception front-end, which in the original work predicts a laser-scan-like representation from monocular images, while the planar envelope parameters configure collision checking for sampled candidate motions. Because the planner reasons only about the declared configuration, the same stack can be deployed on wheeled, legged, and other platforms. The present work keeps AgniNav’s configuration interface, candidate generation, and envelope-based collision checking, but replaces its perception input with a range predictor that carries calibrated uncertainty, and adds a modulation layer that changes the margin and speed limit in response to that uncertainty. AgniNav’s configuration is static; ours is augmented by a time-varying, uncertainty-dependent margin that is added to the declared envelope.

CeRLP [16] pursues a related goal by converting heterogeneous visual observations into a unified geometric representation, with scale-corrected depth and height-adaptive scan abstraction, before local planning. Generalist learned policies such as GNM [17], ViNT [18], and NoMaD [19] instead share knowledge across robots by training on pooled multi-robot data with standardized action spaces. These systems emphasize transfer across bodies; none of them exposes a calibrated measure of geometric uncertainty to the action-selection stage, which is the interface studied here. Classical sampling-based local planners, such as the path-library planner of the CMU exploration environment [20] and gradient-based planners such as EGO-Planner [21], assume that the occupancy or range input is correct up to a fixed inflation radius. Hu et al. [22] learn context-dependent clearance budgets for visual navigation, which addresses the same static-margin problem from a learning perspective; the margin here is instead a closed-form function of calibrated uncertainty, which makes its behavior in the limit of vanishing uncertainty analyzable.

2.2 Future-range perception and legged navigation

FutureRay [11] predicts the free range that a quadruped will have along its own predicted, control-aligned directions at future times, rather than predicting a full occupancy map and

querying it afterwards. The key observation is that, for an agile robot, the relevant geometric question is not “where are the obstacles” but “how far can the robot travel along the direction a given command will take it, at the time it gets there”. The predictor in this paper adopts that query structure directly. It departs from FutureRay in its output: in addition to a point estimate, it returns a heteroscedastic scale that is subsequently recalibrated (Sec. 4.3), and it is trained on synthetically degraded sensor data. FutureRay’s point predictions are therefore the special case that the nominal policy π_0 of Sec. 3 consumes.

On the locomotion side, massively parallel reinforcement learning [23] and teacher–student training with privileged terrain information [2, 3] produced robust velocity-tracking policies for ANYmal, which the present planner commands. Rudin et al. [24] and Hoeller et al. [25] learn locomotion and local navigation jointly, reaching high agility in structured obstacle courses; these approaches embed perception uncertainty implicitly in the policy and provide no explicit handle on margins. ArtPlanner [26] plans over elevation maps with learned reachability and was hardened through field deployment, and model-predictive approaches [27] couple perceptive terrain models with whole-body optimization. These planners rely on GPU elevation mapping [28], which fuses range data with explicit variance estimates; that variance, however, models sensor noise and localization drift rather than the structured failure modes of dust or darkness. Frey et al. [29] learn traversability online from visual features, a complementary signal to the geometric range considered here.

2.3 Perception under degradation

Adverse-weather perception has been studied primarily in automotive settings. Bijelic et al. [7] fuse camera, LiDAR, radar, and gated imaging to remain functional in unseen fog and snow, and physically based simulation of fog [8] and snowfall [30] on real point clouds has become a standard augmentation for robust detection. Heinzler et al. [9] learn to remove weather-induced points from LiDAR scans. The synthetic degradation used in this paper follows the same physical intuition (attenuation along the beam plus near-range backscatter), but its purpose differs: rather than restoring a clean point cloud, the predictor is trained to report how uncertain its range estimate is. In robotics, the DARPA Subterranean Challenge exposed legged and aerial systems to dust, smoke, and darkness [4, 5], and the resulting systems relied on multi-modal, IMU-centric odometry [31] and resilient SLAM [6]. Those works focus on state estimation under degradation; this paper focuses on the local planner’s reaction to degraded geometry. STEP [32] is closest in spirit, using conditional value-at-risk over traversability uncertainty for off-road planning; it targets terrain risk for wheeled and legged platforms at mapping scale rather than control-aligned free range at reactive scale.

2.4 Predictive uncertainty and calibration

Kendall and Gal [12] distinguish aleatoric uncertainty, modeled by a heteroscedastic output head trained with a likelihood loss, from epistemic uncertainty, approximated by Monte Carlo dropout [33] or deep ensembles [13]. All of these produce scales that need not be calibrated: modern networks tend to be overconfident [14], and recalibration of regression outputs [15] is generally required before such scales can be interpreted as interval widths. Conformal prediction [34] provides finite-sample, distribution-free marginal coverage under

exchangeability, and conformalized quantile regression [35] adapts interval widths to the input. The calibration step here is a normalized split-conformal procedure applied separately within strata of an observable degradation index; stratification is the design choice that keeps the coverage statement meaningful when the degradation regime shifts during a run.

2.5 Uncertainty-aware planning and safety filters

Kahn et al. [37] reduce speed in proportion to the predicted uncertainty of a learned collision model, and Lütjens et al. [38] use ensemble and dropout uncertainty to make a reinforcement-learning navigation policy more cautious in novel situations. Both demonstrate the value of uncertainty-dependent caution, but neither guarantees that the cautious policy collapses to the nominal one when uncertainty is low, and neither calibrates the uncertainty. Lindemann et al. [36] use conformal prediction regions for predicted agent trajectories as constraints in model-predictive planning, obtaining probabilistic safety guarantees; the present work applies a similar conformal argument to range predictions of the robot's own free space. Safety filters, including control barrier functions [39], predictive safety filters [40], and the unified view of Hsu et al. [41], minimally modify a nominal command to satisfy a safety constraint. The modulation law of Sec. 4.5 is a filter in this sense, with the distinguishing feature that its activation is gated by calibrated excess uncertainty rather than by proximity to a known constraint boundary.

2.6 Simulation infrastructure

Training and the simulated evaluation use Isaac Lab, the successor of the Orbit framework [43], built on GPU-parallel physics in the lineage of Isaac Gym [42]. GPU parallelism makes it practical both to generate large calibration sets under many degradation settings and to run the evaluation sweep of Sec. 5.

03 Problem Formulation

3.1 Robot, configuration, and commands

The robot is a quadruped whose locomotion controller tracks planar body-frame velocity commands $u = (v_x, v_y, \omega) \in \mathcal{U}(c)$ at 50 Hz, where c is the AgniNav configuration. The configuration contains the planar collision envelope (l_f, l_r, w) , the collision-relevant height h , and the admissible command set $\mathcal{U}(c)$ defined by velocity and acceleration limits. The local planner runs with period $\Delta t = 50$ ms. At planning step t , it chooses among K candidate commands $\{u_k\}_{k=1}^K \subset \mathcal{U}(c)$, each held constant over a horizon T_h and evaluated at J future times $\tau_j = j T_h / J$, $j = 1, \dots, J$. Under the kinematic roll-out model, candidate k produces a predicted pose

$$(p_k(\tau_j), \psi_k(\tau_j)) = \Phi(p_t, \psi_t, u_k, \tau_j), \quad (1)$$

where $p \in \mathbb{R}^2$ is the planar position, ψ the yaw, and Φ the closed-form integration of a constant body-frame twist.

3.2 Control-aligned range queries

Following FutureRay [11], the geometric quantity of interest is the free range along the direction in which the candidate command moves the body. For a constant body-frame twist, this direction is fixed in the body frame at $\theta_k = \text{atan2}(v_{y,k}, v_{x,k})$; for pure rotations, θ_k is taken as the forward axis. The *control-aligned query* q_{kj} is the ray that starts at $p_k(\tau_j)$ with world bearing $\psi_k(\tau_j) + \theta_k$. Its true free range ρ_{kj} is the distance along q_{kj} to the nearest obstacle surface at time τ_j within the

collision-relevant height band $[0, h]$, clipped at a local range $r_{\max}$.

The body occupies part of every ray. For the rectangular envelope of AgniNav, the distance from the body center to the envelope boundary along body-frame bearing θ is

$$d(\theta; c) = \min \left\{ \frac{\ell(\theta)}{|\cos \theta|}, \frac{w}{|\sin \theta|} \right\}, \quad (2)$$

$$\ell(\theta) = \begin{cases} l_f, & \cos \theta \geq 0, \\ l_r, & \cos \theta < 0, \end{cases}$$

with the convention that a term with a zero denominator is $+\infty$. The true clearance of query q_{kj} is $g_{kj} = \rho_{kj} - d(\theta_k; c)$; candidate k is collision-free along its control-aligned queries if $g_{kj} > 0$ for all j .

3.3 Observations and degradation

At each step, the robot receives an observation O_t consisting of a LiDAR range image with per-return intensity and validity mask, depth images from body-mounted cameras, and proprioceptive state s_t (base twist and gravity direction). Degradation acts on O_t through three channels, which match the axes swept in the evaluation: dust opacity $\eta \in [0, 0.8]$, which attenuates returns and creates near-range backscatter; illuminance $E \in [50, 800]$ lx, which degrades stereo depth; and range dropout $\zeta \in [0, 0.4]$, the fraction of the range image that is missing. The degradation parameters are not observed directly by the planner.

3.4 Planner and requirements

A range predictor supplies estimates $\hat{r}_{kj}$ of ρ_{kj} . The *nominal policy* π_0 is the AgniNav planner evaluated on these point estimates with a fixed margin m_0 : it selects the minimum-cost candidate among those satisfying $\hat{r}_{kj} \geq d(\theta_k; c) + m_0$ for all j , and limits speed with a braking-distance cap (Sec. 4.5). The objective is an uncertainty-aware policy π_U that additionally receives envelope half-widths δ_{kj} and satisfies three requirements:

R1 (nominal recovery). If all half-widths are at or below a threshold, π_U outputs exactly what π_0 outputs, and it returns to π_0 in finite time after the uncertainty subsides.

R2 (envelope-conditional clearance). Whenever the true range of a selected query lies inside its calibrated envelope, the true clearance of that query is non-negative.

R3 (graceful modulation). Margin and speed limit depend continuously, and Lipschitz-continuously, on the uncertainty in excess of the threshold.

04 Method

4.1 Overview

Each planning cycle executes the following pipeline: (1) compute an observable degradation index and select a calibration stratum; (2) generate K candidates from the AgniNav configuration; (3) evaluate the range predictor on all $K \times J$ control-aligned queries in one batch; (4) convert the raw scales into calibrated half-widths; (5) compute excess uncertainty, the widened margin, and feasibility per candidate; (6) select the candidate with the AgniNav cost; and (7) apply the speed cap and send the command to the locomotion controller. The design keeps the AgniNav structure intact so that the nominal policy is literally a special case of the uncertainty-aware one.

4.2 Future-range predictor

The predictor f_ϕ follows FutureRay’s query structure. A convolutional encoder processes the LiDAR range image (range, intensity, and validity channels) and the depth images projected into the same polar grid, producing a feature map F_t . For each query, a small decoder receives features sampled from F_t along bearing θ_k , the proprioceptive state s_t , the command u_k , and the query time τ_j , and outputs

$$(\hat{r}_{kj}, \log \sigma_{kj}) = f_\phi(F_t, s_t, u_k, \tau_j). \quad (3)$$

The network is trained in simulation with ground-truth ranges ρ_{kj} obtained by ray casting against undegraded geometry, using the heteroscedastic Gaussian negative log-likelihood [12] with an additional ℓ_1 term that stabilizes the mean when σ is large:

$$\mathcal{L}(\phi) = \sum_{k,j} \left[\frac{(\rho_{kj} - \hat{r}_{kj})^2}{2\sigma_{kj}^2} + \log \sigma_{kj} + \lambda |\rho_{kj} - \hat{r}_{kj}| \right]. \quad (4)$$

Training observations are degraded synthetically. Dust is modeled per beam by Beer–Lambert attenuation, under which a return from range ρ survives with probability $\exp(-2\mu\rho)$ for an extinction coefficient μ derived from opacity, together with spurious backscatter returns at short range; low illuminance is modeled as range-dependent noise and invalid pixels in stereo depth; dropout removes contiguous azimuth sectors. Because the supervision target is the clean range, σ_{kj} learns to grow wherever the degraded input is uninformative about it.

4.3 Degradation-stratified conformal calibration

The scale σ_{kj} is a learned quantity with no coverage guarantee, and its calibration typically differs between clear and degraded inputs [14]. It is therefore recalibrated by normalized split conformal prediction [34], stratified by an observable degradation index

$$\xi_t = w_1 \bar{\zeta}_t + w_2 \bar{b}_t + w_3 (1 - \bar{I}_t) \in [0, 1], \quad (5)$$

where $\bar{\zeta}_t$ is the fraction of invalid range pixels, $\bar{b}_t$ the fraction of returns closer than the body envelope plus 0.5 m (a backscatter proxy), $\bar{I}_t$ the normalized mean image brightness, and $w_1 + w_2 + w_3 = 1$. The interval $[0, 1]$ is partitioned into B strata. For a held-out calibration set $\mathcal{D}_b$ of n_b queries in stratum b , generated in simulation under the same degradation model but disjoint scenes and seeds from training, the nonconformity scores and stratum quantile are

$$s_i = \frac{|\rho_i - \hat{r}_i|}{\sigma_i}, \quad \hat{q}_b = s_{(\lceil (n_b+1)(1-\alpha) \rceil)}, \quad (6)$$

where $s_{(m)}$ denotes the m -th smallest score in $\mathcal{D}_b$. At run time, with b_t the stratum of ξ_t , the calibrated half-width and envelope are

$$\delta_{kj} = \hat{q}_{b_t} \sigma_{kj}, \quad \mathcal{E}_{kj} = [\hat{r}_{kj} - \delta_{kj}, \hat{r}_{kj} + \delta_{kj}]. \quad (7)$$

If a test query is exchangeable with the calibration queries of its stratum, the standard conformal argument gives $\Pr(\rho_{kj} \in \mathcal{E}_{kj}) \geq 1 - \alpha$ [34]. Stratification matters because a single global quantile would be dominated by the abundant clear-condition data, producing envelopes that are too wide in clear air and too narrow in dust. Only the lower bound of $\mathcal{E}_{kj}$ is safety-relevant; a two-sided score is retained because it is less sensitive to backscatter-induced underestimates being mistaken for confident predictions.

4.4 Control-aligned excess uncertainty

Prediction uncertainty grows with the look-ahead time even in clear conditions. The threshold is therefore time-dependent,

$$\delta_{\text{th}}(\tau) = \delta_0 + \gamma \tau, \quad (8)$$

and only the part of the half-width above it is treated as excess. The per-query and per-candidate excess uncertainties are

$$e_{kj} = [\delta_{kj} - \delta_{\text{th}}(\tau_j)]_+, \quad e_k = \max_j e_{kj}, \quad (9)$$

with $[x]_+ = \max(x, 0)$. Using the maximum over the horizon makes the candidate as uncertain as its least certain query, which is the conservative choice for a collision constraint.

4.5 Margin widening and candidate selection

The safety margin of candidate k is

$$m_k = m_0 + \kappa_m e_k, \quad \kappa_m \geq 1, \quad (10)$$

and the candidate is feasible if

$$\hat{r}_{kj} \geq d(\theta_k; c) + m_k \quad \text{for all } j = 1, \dots, J. \quad (11)$$

Among feasible candidates, the planner minimizes the AgniNav cost

$$\begin{aligned} J_k = & w_g \|p_k(T_h) - g_t\| + w_\psi |\psi_k(T_h) - \psi_{g,t}| \\ & + w_c \sum_j \exp\left(-\frac{\hat{r}_{kj} - d(\theta_k; c) - m_k}{\ell_c}\right) \\ & + w_s \|u_k - u_{t-1}\|^2, \end{aligned} \quad (12)$$

where g_t and $\psi_{g,t}$ are the local goal position and heading, ℓ_c is a clearance length scale, and u_{t-1} is the previous command. Ties are broken by candidate index. If no candidate is feasible, the planner commands zero translational velocity and rotates in place toward the bearing that maximizes $\hat{r} - \delta$, which is AgniNav’s recovery behavior evaluated on the envelope lower bound. Margin widening enters both the hard constraint (11) and the soft clearance term of (12), so uncertainty affects not only which candidates are admissible but also how strongly the planner prefers to stay away from uncertain geometry.

The condition $\kappa_m \geq 1$ is what makes the widened margin cover the excess uncertainty one-for-one; it is used in Proposition 2. An alternative design subtracts the excess from the predicted range instead of adding it to the margin; the two are equivalent in (11) for $\kappa_m = 1$, and the margin form was chosen because it composes directly with AgniNav’s envelope-plus-margin interface.

4.6 Speed modulation

Speed is modulated by a scalar excess $\bar{E}_t$ attached to the selected candidate k^* , with fast attack and linear release:

$$\bar{E}_t = \max(e_{k^*}, \bar{E}_{t-1} - \varrho \Delta t), \quad \bar{E}_t \geq 0. \quad (13)$$

Linear rather than exponential release is deliberate: it reaches zero in finite time, which Proposition 1 requires, and it prevents chattering when the uncertainty hovers around threshold. The speed limit is

$$\bar{v}_t = \min \left\{ v_{\text{set}}, v_{\text{set}} \max(v_{\min}, 1 - \kappa_v \bar{E}_t), v_b(\chi_{k^*}) \right\}, \quad (14)$$

where v_{set} is the operator setpoint, $v_{\text{min}} \in (0, 1)$ a floor on the uncertainty-driven reduction, and v_b a braking-distance cap evaluated on the selected candidate's smallest margin-adjusted clearance $\chi_k = \min_j (\hat{r}_{kj} - d(\theta_k; c) - m_k)$. With deceleration a_b and reaction delay t_d , the largest speed from which the robot can stop within distance $\chi \geq 0$ is

$$v_b(\chi) = -a_b t_d + \sqrt{a_b^2 t_d^2 + 2a_b \chi}. \quad (15)$$

The floor v_{min} applies only to the uncertainty term; the braking cap can still bring the robot to rest, because $v_b(0) = 0$. The commanded twist is the selected candidate u_{k^*} with its translational part scaled so that its norm does not exceed $\bar{v}_t$, keeping its direction, and hence the control-aligned bearing θ_{k^*} , unchanged.

4.7 Properties

PROPOSITION 1 (EXACT NOMINAL RECOVERY)

Suppose that $\delta_{kj} \leq \delta_{\text{th}}(\tau_j)$ for all k, j at every planning step from time t_0 onward. Then, given identical inputs, π_U selects the same candidate as π_0 at every such step, and it issues the same command as π_0 at every step $t \geq t_0 + \bar{E}_{t_0-1}/\rho$. In particular, if all half-widths are at or below threshold and $\bar{E}_{t-1} = 0$, the two commands coincide at step t .

Proof. Under the hypothesis, $e_{kj} = 0$ by (9), so $e_k = 0$ and $m_k = m_0$ for all k . Then (11) and (12) coincide with the feasibility test and cost of π_0 , and with the same tie-breaking the same k^* is selected; the recovery behavior coincides as well, since it applies only when no candidate is feasible, which is the same event for both policies. By (13), with $e_{k^*} = 0$ the excess decreases by $\rho \Delta t$ per step until it reaches zero, which takes at most $\bar{E}_{t_0-1}/\rho$ seconds. Once $\bar{E}_t = 0$, the middle term of (14) equals v_{set} and the braking term is evaluated with $m_{k^*} = m_0$, which is exactly the speed limit of π_0 . $\square$

Because $\delta_{kj} = \hat{q}_b \sigma_{kj}$, the hypothesis holds in particular whenever $\sigma_{kj} < \delta_0/\hat{q}_b$ for all queries, so $\pi_U \rightarrow \pi_0$ as the predicted scale vanishes. The recovery is exact, not asymptotic: below threshold, the uncertainty-aware machinery is inactive.

PROPOSITION 2 (ENVELOPE-CONDITIONAL CLEARANCE)

Assume $\kappa_m \geq 1$ and $m_0 \geq \delta_{\text{th}}(T_h)$. If candidate k is feasible in the sense of (11) and $\rho_{kj} \in \mathcal{E}_{kj}$, then $g_{kj} \geq m_0 - \delta_{\text{th}}(\tau_j) \geq 0$.

Proof. By (9), $e_k \geq e_{kj} \geq \delta_{kj} - \delta_{\text{th}}(\tau_j)$. Using $\rho_{kj} \geq \hat{r}_{kj} - \delta_{kj}$, (11), and (10), $g_{kj} \geq \hat{r}_{kj} - \delta_{kj} - d(\theta_k; c) \geq m_0 + \kappa_m e_k - \delta_{kj} \geq m_0 + e_k - \delta_{kj} \geq m_0 - \delta_{\text{th}}(\tau_j)$, and the last quantity is non-negative because δ_{th} is increasing and $m_0 \geq \delta_{\text{th}}(T_h)$. $\square$

Combined with the conformal guarantee, every query of the executed candidate has non-negative true clearance with probability at least $1 - \alpha$ within its stratum. The guarantee is per query; a joint statement over all J queries by the union bound, $1 - J\alpha$, is vacuous for the parameters of Table 1. The bound is also conditional on exchangeability, which real degradation can violate (Sec. 7).

Table 1: Planner and predictor configuration on ANYmal.

Symbol	Meaning	Value
Δt	Planner period	50 ms (20 Hz)
T_h, J	Horizon, query steps	2.0 s, 20
K	Candidate commands	48
r_{max}	Local query range	10 m
(l_f, l_r, w, h)	AgniNav envelope	(0.50, 0.50, 0.30, 0.75) m
m_0	Nominal margin	0.15 m
δ_0, γ	Threshold offset, slope	0.08 m, 0.03 m/s
κ_m	Margin gain	1.2
κ_v, v_{min}	Speed gain, floor	1.5 m^{-1} , 0.3
ρ	Release rate	0.2 m/s
a_b, t_d	Braking decel., delay	2.0 m/s^2 , 0.15 s
α, B	Miscoverage, strata	0.05, 5

PROPOSITION 3 (LIPSCHITZ MODULATION)

As functions of the excess, m_k is κ_m -Lipschitz in e_k , the uncertainty term of (14) is $v_{\text{set}}\kappa_v$ -Lipschitz in $\bar{E}_t$, and the braking cap $v_b(\chi_k)$ is $(1 + \kappa_m)/t_d$ -Lipschitz in e_k wherever $\chi_k \geq 0$.

Proof. The first two claims follow because $[\cdot]_+$, $\max$, and $\min$ are 1-Lipschitz. For the third, $v'_b(\chi) = a_b/\sqrt{a_b^2 t_d^2 + 2a_b \chi} \leq 1/t_d$ for $\chi \geq 0$, and χ_k changes by at most κ_m per unit change of e_k through m_k and by one per unit change of a predicted range, so $v_b(\chi_k)$ changes by at most $(1 + \kappa_m)/t_d$ per unit change of e_k . $\square$

Proposition 3 rules out jumps in the margin and speed limit as uncertainty crosses the threshold. It does not make the selected candidate continuous; the arg min over a finite set can switch discretely, as in any sampling-based planner. The smoothness term w_s in (12) and the hysteresis (13) damp such switches in practice.

4.8 Implementation

Table 1 lists the configuration used on ANYmal. The envelope values include the onboard sensor housings. The margin m_0 and threshold satisfy the condition of Proposition 2, $m_0 = 0.15 \text{ m} \geq \delta_{\text{th}}(T_h) = 0.14 \text{ m}$. The predictor evaluates all $KJ = 960$ queries of a cycle in one batch on the onboard computer, and the range image is cropped to r_{max} for local planning, although the LiDAR itself measures to substantially longer range.

05 Experimental Setup

5.1 Platform

All experiments use an ANYmal quadruped with its onboard rotating LiDAR and body-mounted depth cameras. The planner of Sec. 4 sends velocity commands to a learned locomotion controller that tracks them at 50 Hz. The same AgniNav configuration (Table 1) is used in simulation and on hardware.

5.2 Simulation protocol

Simulated evaluation runs in Isaac Lab with ANYmal in 15 scenes. Synthetic perception degradation is swept along three axes (Table 2): dust opacity from 0 to 80%, illuminance from 50 to 800 lx, and range dropout from 0 to 40%. Each scene is evaluated with 5 seeds and 30 trials per seed, i.e., $15 \times 5 \times 30 = 2,250$ trials per method. The calibration data of Sec. 4.3 are drawn from scenes and seeds disjoint from the evaluation set.

Table 2: Evaluation protocol.

Item	Setting
Simulator	Isaac Lab, ANYmal
Scenes	15
Dust opacity	0–80%
Illuminance	50–800 lx
Range dropout	0–40%
Repetitions	5 seeds $\times$ 30 trials per scene
Real environments	Dusty warehouse bay; dim parking structure
Real runs	10 per environment, setpoints 1.0–2.5 m/s

5.3 Real-world protocol

Hardware trials take place in two environments that instantiate the degradation channels physically: a dusty warehouse bay and a dim parking structure. ANYmal performs 10 runs per environment at speed setpoints between 1.0 and 2.5 m/s, for 20 runs in total.

5.4 Baselines and ablations

All methods share the AgniNav backbone, candidate set, locomotion controller, and predictor point estimates, so that differences isolate the treatment of uncertainty.

- **Nominal planner (no uncertainty):** π_0 , i.e., margin m_0 and the braking cap, with δ_{kj} ignored.
- **Fixed $1.5\times$ margin inflation:** π_0 with m_0 replaced by $1.5 m_0 = 0.225$ m everywhere.
- **Uncertainty margin, no speed reduction:** a margin proportional to the full calibrated half-width, $m_k = m_0 + \kappa_m \max_j \delta_{kj}$, without threshold, hysteresis, or uncertainty-dependent speed limit.
- **Ours:** the full method of Sec. 4.

The ablations remove one component of the full method at a time: *w/o calibrated uncertainty envelopes* replaces $\hat{q}_b$ by the Gaussian quantile 1.96 applied to the raw σ_{kj} ; *w/o speed reduction branch* removes the uncertainty term of (14) and evaluates the braking cap with m_0 ; and *w/o margin widening* sets $\kappa_m = 0$ while keeping the speed branch.

5.5 Metrics

Success rate is the percentage of trials that reach the goal without collision and before timeout. *Mean speed* is path length divided by elapsed time, averaged over trials, with collided and timed-out trials included up to termination. *Collision-free distance* is total distance traveled divided by the number of collisions, in km per collision. *Clean-regime parity* is measured on undegraded trials (zero opacity and dropout, full illumination): it is the method’s success-weighted mean speed expressed as a percentage of that of π_0 supplied with privileged ground-truth ranges ρ_{kj} in place of predictions. Parity thus measures how much a method gives up in clear conditions relative to a planner with perfect range knowledge. Clear conditions are not uncertainty-free: occlusions, thin structures, and fast turns still produce above-threshold half-widths, so parity below 100% is expected even for π_0 .

06 Results

6.1 Main comparison

Table 3 reports the aggregate results over the evaluation protocol of Sec. 5. The uncertainty-aware planner reaches a success rate of 87.9%, which is 11.0 percentage points above the

nominal planner (76.9%), 5.4 points above fixed $1.5\times$ margin inflation (82.5%), and 7.1 points above the uncertainty margin without speed reduction (80.8%). It also achieves the highest collision-free distance, 3.8 km per collision versus 3.4 for the nominal planner (about 12% more distance per collision), and the highest clean-regime parity, 99.2%.

Three patterns in Table 3 deserve comment. First, fixed inflation improves success over the nominal planner (82.5% vs. 76.9%) but costs 10.9 points of clean-regime parity (83.6% vs. 94.5%) and does not reduce the collision rate: its collision-free distance, 3.2 km per collision, is the lowest of the four methods. This is the trade-off that motivates the method. A constant margin is paid for in every clear-air trial, while in degraded conditions the actual range error can still exceed it (Sec. 6.3). A plausible reason for the lower collision-free distance is that the inflated margin renders narrow passages infeasible and forces more detours and in-place recovery rotations in clutter; the recorded data do not decompose collisions by cause, so this explanation is not confirmed.

Second, an uncertainty-proportional margin without threshold and speed modulation improves collision-free distance (3.6 vs. 3.4 km per collision) but gains less success than fixed inflation (80.8%) and gives up 1.5 points of parity relative to the nominal planner (93.0% vs. 94.5%). Because it reacts to the full half-width rather than the excess, it is active even in clear conditions, which is consistent with its lower parity.

Third, the full method is faster on average than every baseline (1.94 m/s versus 1.80–1.82 m/s, an increase of 0.12 m/s or about 6.6% over the nominal planner), even though its only speed-related change is a reduction. Since mean speed includes time spent in stops and recovery maneuvers, the most likely explanation is that early, graded deceleration in uncertain regions avoids the abrupt infeasibility events, in which every candidate is rejected at once and the planner halts and rotates, that occur when a confident point prediction is suddenly contradicted. The data reported here do not include a breakdown of stop events, so this explanation is offered as a hypothesis. The higher clean-regime parity of the full method relative to π_0 (99.2% vs. 94.5%) is consistent with the same mechanism acting on the residual above-threshold uncertainty that exists in undegraded scenes.

6.2 Ablation

Table 4 isolates the three components. Every component contributes, and the largest effect comes from calibration: without calibrated envelopes, success falls by 13.9 points to 74.0%, which is 2.9 points below the nominal planner that ignores uncertainty altogether. Raw heteroscedastic scales are therefore not merely less useful than calibrated ones; acting on them is harmful. A likely mechanism, consistent with the known miscalibration of learned scales [14, 15] but not separately measured here, is that a single fixed quantile is overconfident in heavily degraded strata, so the planner neither widens its margin nor slows down where it should, and underconfident in clear strata, so it triggers margin widening and speed reduction unnecessarily; the stratified quantiles of (6) are designed to correct both errors. Removing margin widening lowers success by 9.7 points to 78.2%, and removing the speed-reduction branch lowers it by 7.3 points to 80.6%. The geometric branch thus matters somewhat more than the speed branch, but neither alone recovers the full result, which supports coupling the two through a single excess-uncertainty signal.

Table 3: Main comparison. All methods share the AgniNav backbone and predictor point estimates.

Method	Success rate (%)	Mean speed (m/s)	Collision-free distance (km per collision)	Clean-regime parity (%)
Nominal planner (no uncertainty)	76.9	1.82	3.4	94.5
Fixed 1.5x margin inflation	82.5	1.81	3.2	83.6
Uncertainty margin, no speed reduction	80.8	1.80	3.6	93.0
Ours	87.9	1.94	3.8	99.2

Table 4: Ablation of the uncertainty-aware planner.

Variant	Success rate (%)
Ours (uncertainty-aware)	87.9
w/o calibrated uncertainty envelopes	74.0
w/o speed reduction branch	80.6
w/o margin widening	78.2

The ablation *w/o speed reduction branch* (80.6%) and the baseline *uncertainty margin, no speed reduction* (80.8%) differ in their margin law: the former retains the threshold-gated excess margin of (10), while the latter uses a margin proportional to the full half-width. Their success rates are within 0.2 points of each other, so on this metric the threshold gating by itself does not account for the gain of the full method; its benefit appears in combination with the speed branch, and in the clean-regime parity of the full method.

6.3 Recorded failure cases

Three recorded events illustrate how the mechanism behaves at the edges of its operating range.

Dust at 62% opacity

In the dusty warehouse bay at 62% opacity, the fixed-margin baseline collided once; the range error at the time of contact was 0.3 m. With the configuration of Table 1, the inflated margin was $1.5m_0 = 0.225$ m, so the error exceeded it by 0.075 m: a constant margin protects only against errors smaller than itself. Under the same conditions, the uncertainty-aware planner reduced speed to 1.4 m/s and cleared the obstacle with an 18 cm margin. The episode illustrates the intended division of labor: the widened margin accounted for the enlarged envelope, and the speed cap bounded the consequence of residual error.

Illuminance of 50 lx

At the lowest illuminance in the sweep, 50 lx, the uncertainty envelope of the future-range predictor widened by a factor of 4.2. By construction of (9)–(14), a wider envelope produces wider margins and a lower speed limit. When the envelope normalized, the planner’s nominal policy recovered to 99.2% parity, the clean-regime value in Table 3. This is the behavior that Proposition 1 predicts: once half-widths are below threshold and the speed excess has been released, the uncertainty-aware machinery is inactive, and no residual conservatism persists.

9 s dropout in the parking structure

In one parking-structure run, a LiDAR re-alignment event caused a 9 s dropout. The speed-reduction branch held throughout the event, no incident occurred, and the run covered 41 m. During a dropout, the validity channel of the range image marks the missing sectors, the degradation index (5) moves to a higher stratum, and the half-widths of queries through the missing sectors grow; the hysteresis (13) prevents the speed limit from rebounding during brief intervals of partial data. The event also marks a limit of the approach: the planner continued

on the basis of the depth cameras and the predictor’s learned prior over a 9 s interval without LiDAR, and the absence of an incident in a single event is not evidence that longer outages would be handled safely.

6.4 Discussion

Taken together, the results support three conclusions about margin behavior under degradation. Margins should scale with calibrated uncertainty rather than being fixed, because a fixed margin is simultaneously too large in clear conditions (parity of 83.6%) and too small for the errors that dust can produce (the 0.3 m error above). Uncertainty should be calibrated before it is used, because an uncalibrated signal performs worse than none (74.0% vs. 76.9%). And the modulation should be gated at a threshold with exact recovery, because a planner that reacts to all uncertainty forgoes clean-regime performance (93.0% parity), whereas the threshold-gated planner retains 99.2%.

07 Limitations

The coverage statement of Sec. 4.3 holds per query, within a stratum, and under exchangeability between calibration and deployment data. The calibration data are simulated, and the synthetic dust and low-light models are approximations; physical dust plumes are spatially inhomogeneous and temporally correlated, which violates exchangeability. The guarantee should therefore be read as a design rationale for the hardware experiments rather than a certified bound. The union bound over the J queries of a candidate is vacuous at the chosen α , so the method does not provide a trajectory-level probabilistic guarantee.

The real-world evaluation comprises 20 runs in two environments, a small sample relative to the 2,250 simulated trials per method. It shows that the system operates on hardware under physical degradation, and the recorded events are consistent with the simulated findings, but it is too small to establish that the simulated advantage transfers quantitatively. The explanations offered for the higher mean speed of the full method and for the lower collision-free distance of fixed inflation are hypotheses that the recorded data do not test. The thresholds, gains, and stratum boundaries were set by hand; the sensitivity of the results to them was not characterized. Finally, the method addresses range degradation only. It does not model localization drift, terrain-induced locomotion failures, or dynamic obstacles, and it inherits the assumption of the control-aligned formulation that a constant-twist rollout adequately represents the robot’s motion over the 2 s horizon.

08 Conclusion

This paper presented a local planner for quadrupeds that couples the AgniNav configuration-driven backbone with a FutureRay-style predictor of control-aligned future range whose uncertainty envelopes are recalibrated by degradation-stratified conformal prediction. A threshold-gated modulation law widens safety margins and caps speed in proportion to

excess calibrated uncertainty, recovers the nominal policy exactly and in finite time when uncertainty subsides, guarantees non-negative clearance whenever the true range lies inside its envelope, and varies Lipschitz-continuously with the excess. Across the evaluation protocol on ANYmal, the planner reached 87.9% success, a mean speed of 1.94 m/s, 3.8 km per collision, and 99.2% clean-regime parity, improving on nominal, fixed-inflation, and uncertainty-proportional baselines; the ablation identified calibration as the most important component. Hardware runs in a dusty warehouse bay and a dim parking structure exercised the mechanism under physical degradation. Future work will address trajectory-level guarantees under non-exchangeable degradation, online recalibration from hardware data, and a systematic characterization of sensitivity to the modulation parameters.

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