

ATOM-CBF: Adaptive Safe Perception-Based Control under Out-of-Distribution Measurements

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Abstract

Ensuring the safety of real-world systems is challenging, especially when they rely on learned perception modules to infer the system state from high-dimensional sensor data. These perception modules are vulnerable to epistemic uncertainty, often failing when encountering out-of-distribution (OoD) measurements not seen during training. To address this gap, we introduce ATOM-CBF (Adaptive-To-OoD-Measurement Control Barrier Function), a novel safe control framework that explicitly computes and adapts to the epistemic uncertainty from OoD measurements, without the need for ground-truth labels or information on distribution shifts. Our approach features two key components: (1) an OoD-aware adaptive perception error margin and (2) a safety filter that integrates this adaptive error margin, enabling the filter to adjust its conservatism in real-time. We provide empirical validation in simulations, demonstrating that ATOM-CBF maintains safety for an F1Tenth vehicle with LiDAR scans and a quadruped robot with RGB images.

Keywords: Safe Control, Adaptive Control, Perception-Based Control, Epistemic Uncertainty

1. Introduction

The problem of uncertainty lies at the heart of ensuring safety for autonomous systems in complex, real-world environments. While a vast body of work provides safety guarantees for systems under uncertainties in their dynamics or parameters (Xiao et al., 2021; Lopez and Slotine, 2023; Yun et al., 2025), this line of work often builds on a fundamental reliance on state information. In practice, states are not given in real-world deployment. Instead, they must be inferred from high-dimensional sensor measurements, such as camera images or LiDAR point clouds, often using learned perception modules, e.g., deep neural network (DNN)-based. These modules introduce their own critical source of uncertainty. To date, much of the field has focused on addressing safe perception-based control under *aleatoric* uncertainty, e.g., stochastic noise inherent to sensors (Cosner et al., 2022; Yang et al., 2023). However, learned perception modules remain vulnerable to *epistemic* uncertainty, i.e., the model’s own lack of knowledge, which arises when encountering novel, out-of-distribution (OoD) data not seen during training (Park et al., 2024a,b, 2025).

While epistemic uncertainty can be reduced by training the model on more diverse data (Tobin et al., 2017; Hendrycks et al., 2020), this approach is inherently limited, as it is untenable to capture the full distribution of all real-world scenarios. Frameworks that provide safety guarantees under OoD measurements often require new ground-truth labels to adapt online (Huang et al., 2024) or offline statistical bounds on a distribution of data (Majumdar et al., 2021). These approaches are not designed for a truly on-the-fly safe controller, which has no access to ground-truth labels of a new OoD measurement and information on the distribution shift itself. We address this gap by introducing **ATOM-CBF** (Adaptive-To-OoD-Measurement Control Barrier Function), a novel safe

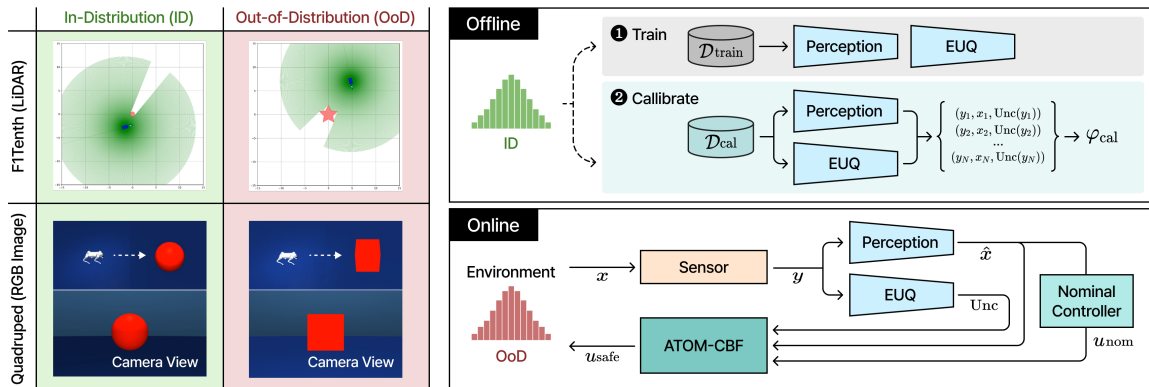


Figure 1: Problem setting (left) and ATOM-CBF (right). Offline, ID data is used to train a perception module and an epistemic uncertainty quantification (EUQ) module, and compute the base error ratio, φ_{cal} . Online, ATOM-CBF is deployed in OoD settings for F1Tenth and quadraped experiments.

control framework that explicitly computes and adapts to the epistemic uncertainty from OoD measurements.

Contributions. In this work, we make the following contributions to provide empirical safety assurances for perception-based robotic control in the presence of OoD sensor measurements:

- **OoD-aware adaptive perception error margin.** We introduce an effective calibration method to compute an adaptive error margin that dynamically scales with the epistemic uncertainty of a perception module (Fig. 1, Offline).
- **ATOM-CBF.** We propose the *Adaptive-To-OoD-Measurement Control Barrier Function* (ATOM-CBF), a safety filter that integrates our adaptive error margin to ensure safety when encountering OoD sensor measurements (Fig. 1, Online).
- **Empirical Validation.** We demonstrate the efficacy of ATOM-CBF and provide empirical safety assurances in high-fidelity simulations, including an F1Tenth vehicle with 2D LiDAR scans and a quadraped robot with RGB camera images (Fig. 1, left panel).

2. Related Work

We group prior work on perception-based safety into two strands: (1) guaranteed safety under in-distribution (ID) measurements, i.e., data from the same distribution as the perception module’s training set, and (2) OoD-aware safety.

Safety guarantees for perception-based control (ID). One line of work stems from formal verification, attempting to verify the perception DNN directly (Brown et al., 2022; Wei et al., 2025), to be used with downstream safe controllers. However, these tools often struggle to scale to complex DNNs. Another approach verifies the closed-loop system by abstracting the perception module. Hsieh et al. (2022) use “safe approximate abstractions,” though the link to the real perception module is only empirical. Dean and Recht (2021) provide statistical guarantees but assume linear dynamics. Dawson et al. (2022) present a certificate-based method that relies on an approximate sensor model, making it difficult to scale to high-dimensional sensor data, such as images. A third category integrates perception uncertainty directly into the closed loop to provide robustness. Dean

et al. (2021) provide a control-theoretic formal bound of the worst-case perception error for robust safety. This has been extended to consider aleatoric uncertainty by Yang et al. (2023) using conformal prediction. Dixit et al. (2025) also use conformal prediction to provide robust bounding boxes around perceived obstacles, while other approaches numerically synthesize a safety function from perception data (Toufighi et al., 2024; Bena et al., 2025). A key limitation across these methods is their dependency on bounds derived from ID data, making them vulnerable to OoD measurements.

OoD-aware safety for perception-based systems. A second body of work addresses OoD-aware safety. Some methods seek to return the system to an ID state after an OoD detection. Richter and Roy (2017) revert to safe prior behavior, and Reichlin et al. (2022) use a recovery policy to return to the ID manifold. Other approaches aim to prevent the system from ever entering OoD states. Wellhausen et al. (2020) use anomaly detection to avoid OoD regions in a planner, while Castañeda et al. (2023), Lin et al. (2024), and Seo et al. (2025) use barrier functions or reachability analysis to stay within ID regions. Chakraborty et al. (2024), He et al. (2024), and Contreras et al. (2025) instead use a fallback controller when OoD is detected. However, these methods can fail if OoD entry and measurements are inevitable or the reaction is too late. Finally, some frameworks provide safety guarantees under OoD measurements, but rely on information that may not always be available. Huang et al. (2024) require new ground-truth labels online, and Majumdar and Goldstein (2018) require *a priori* knowledge of the distribution shift bounds.

Our work instead provides empirical safety assurances under OoD measurements without requiring new ground-truth labels or *a priori* distribution knowledge. We achieve this by introducing an OoD-aware adaptive perception error margin that scales in real-time with measured epistemic uncertainty, enabling our safety filter to dynamically adjust its conservatism.

3. Preliminaries

In this section, we provide a concise review of the concepts used to formulate our problem. We first introduce the system model and the notion of safety. Next, we review safe control under learned perception modules using Measurement-Robust CBF (MR-CBF), which provides safety under static, bounded perception errors. Finally, we discuss methods for epistemic uncertainty quantification (EUQ) of DNNs.

3.1. System Model and Safety

To start, consider a nonlinear control-affine system:

$$\dot{x} = f(x) + g(x)u, \quad (1)$$

where $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$ are the state and control input, respectively, and functions $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ and $g : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times m}$ are locally Lipschitz continuous. We define a safe set $\mathcal{C} \subset \mathbb{R}^n$ as the zero-superlevel set of a continuously differentiable function $h : \mathbb{R}^n \rightarrow \mathbb{R}$:

$$\mathcal{C} = \{x \in \mathbb{R}^n : h(x) \geq 0\}. \quad (2)$$

Safety of the system (1) is achieved by ensuring that this set is control invariant, a widely used notion in the safe control literature (Liu and Tomizuka, 2014; Wei and Liu, 2019; Ames et al., 2019).

Notation. \mathbb{R} is the set of real numbers, \mathbb{R}^n is a real vector, \mathcal{L} is a Lie derivative, \mathbb{L} is a Lipschitz constant, and $\|x\|_2$ is the Euclidean norm for a vector x . $\kappa : \mathbb{R} \rightarrow \mathbb{R}$ denotes an extended class \mathcal{K}_∞ function, i.e., a strictly increasing function where $\kappa(0) = 0$, $\lim_{v \rightarrow -\infty} \kappa(v) = -\infty$, and $\lim_{v \rightarrow \infty} \kappa(v) = \infty$.

Definition 1 (*Control Invariance*). Let $x(t)$ denote the state trajectory of (1) for time t with initial state $x(0)$. The set \mathcal{C} is control invariant if for every initial state $x(0) \in \mathcal{C}$, there exists an admissible sequence of control inputs u such that the resulting state trajectory $x(t) \in \mathcal{C}$, $\forall t \geq 0$.

Ames et al. (2017) introduces Control Barrier Function (CBF) as a method to formally guarantee this invariance for (1) by providing a sufficient condition on the function $h(x)$. This condition ensures that for any state $x \in \mathcal{C}$, the set of admissible control inputs u that render the system safe is non-empty.

Definition 2 (*Control Barrier Function (CBF)*). Given a set $\mathcal{C} \subset \mathbb{R}^n$ defined as the zero-superlevel set of a continuously differentiable function $h : \mathbb{R}^n \rightarrow \mathbb{R}$, with 0 a regular value, h is a control barrier function (CBF) for (1) on \mathcal{C} if there exists an extended class \mathcal{K}_∞ function κ such that

$$\sup_{u \in \mathbb{R}^m} \left\{ \underbrace{\frac{\partial h(x)}{\partial x} f(x)}_{\mathcal{L}_f h(x)} + \underbrace{\frac{\partial h(x)}{\partial x} g(x) u}_{\mathcal{L}_g h(x)} \right\} \geq -\kappa(h(x)), \quad \forall x \in \mathcal{C}. \quad (3)$$

Note that the notion of safety depends on state information x . However, in many practical settings, such state information is not readily available and must be inferred from a state-dependent sensor measurement $y \in \mathbb{R}^l$. In our problem setting, we assume that this measurement, e.g., high-dimensional data such as LiDAR scans or camera images, is obtained via a locally Lipschitz continuous sensor map $p : \mathbb{R}^n \rightarrow \mathbb{R}^l$, such that $y = p(x)$. We assume this relationship is deterministic, and note that the challenge of safe control using learned perception modules under stochastic sensor noise is addressed in Yang et al. (2023). A common assumption is the existence of a hypothetical inverse map $q : \mathbb{R}^l \rightarrow \mathbb{R}^n$ that can perfectly recover the state, i.e., $q(p(x)) = x$.

In practice, this map is often unknown. Thus, a learned perception map $\hat{q} : \mathbb{R}^l \rightarrow \mathbb{R}^n$ is used to approximate this ideal inverse map. In this work, we primarily consider deep neural network (DNN) perception maps \hat{q} that are learned from data. Due to limitations in the learned model or deficiencies in the training data, the state estimate is related to the true state via an unknown error function $e : \mathbb{R}^n \rightarrow \mathbb{R}^n$,

$$\hat{x} = \hat{q}(y) = x + e(x), \quad (4)$$

where the error function e is implicitly defined by \hat{q} . This perception error $e(x)$ is the central challenge for perception-based safe control. CBF requires the true state x , but the controller only has access to the estimate \hat{x} . Applying a control input based on \hat{x} without accounting for $e(x)$ can violate the safety constraint.

3.2. Safe Control with Learned Perception Module

To address this gap, Dean et al. (2021) introduces measurement-robust control barrier function (MR-CBF). The MR-CBF framework thus provides a formal method to guarantee safety for systems relying on learned perception modules, provided the perception error is bounded and known.

Definition 3 (*Measurement-Robust Control Barrier Function (MR-CBF)*). Let $\mathcal{C} \subset \mathbb{R}^n$ be the zero-superlevel set of a continuously differentiable function $h : \mathbb{R}^n \rightarrow \mathbb{R}$ with 0 a regular value. Then,

the function h is a measurement-robust control barrier function (MR-CBF) for system (1) on \mathcal{C} with parameter function pair $(a, b) : \mathbb{R}^l \rightarrow \mathbb{R}_+^2$ if there exists an extended class \mathcal{K}_∞ function κ such that

$$\sup_{u \in \mathbb{R}^m} \left\{ \mathcal{L}_f h(\hat{x}) + \mathcal{L}_g h(\hat{x})u - (a(y) + b(y)\|u\|_2) \right\} \geq -\kappa(h(\hat{x})). \quad (5)$$

The terms $a(y)$ and $b(y)$ in (5) create a measurement-dependent ‘‘robustness buffer,’’ forcing the controller to be more conservative to account for the perception error. The key result in Dean et al. (2021) connects these abstract parameters to a concrete perception error bound $\epsilon(y)$, which is static. If the perception error is bounded such that $\|e(x)\|_2 \leq \epsilon(y)$ for all $x \in \mathcal{C}$, and the functions $\mathcal{L}_f h$, $\mathcal{L}_g h$, and $\kappa \circ h$ are Lipschitz continuous on \mathcal{C} with Lipschitz coefficients $\mathbb{L}_{\mathcal{L}_f h}$, $\mathbb{L}_{\mathcal{L}_g h}$, and $\mathbb{L}_{\kappa \circ h}$, respectively, then safety is guaranteed by setting $a(y) = \epsilon(y)(\mathbb{L}_{\mathcal{L}_f h} + \mathbb{L}_{\kappa \circ h})$ and $b(y) = \epsilon(y)\mathbb{L}_{\mathcal{L}_g h}$.

Remark 4 *The MR-CBF framework provides robustness by assuming a known, static error bound $\epsilon(y)$. This approach is effective for systems that deal with ID data or for handling aleatoric uncertainty, i.e., sensor noise. However, it does not account for epistemic uncertainty. This becomes critical when a perception module encounters novel OoD measurements, as the true error can far exceed the assumed $\epsilon(y)$, leading to safety violations. Furthermore, the validation of these formal error bounds in prior work has centered on classical models like Kernel Ridge Regression or constant offsets, not the high-dimensional DNNs that are highly susceptible to such OoD failures.*

3.3. Epistemic Uncertainty Quantification for Learned Perception Modules

To address the gap identified in Remark 4, the downstream safe controller must be able to account for epistemic uncertainty of OoD measurements in real-time. This requires an associated epistemic uncertainty quantification (EUQ) module, $\text{Unc} : \mathbb{R}^l \rightarrow \mathbb{R}_+$. This module must produce a scalar score $\text{Unc}(y)$ that is low for ID measurements and high for OoD measurements. We focus on two prominent EUQ modules that represent a key trade-off: Deep Ensembles as a high-performance module, and SCOD as a computationally-efficient, post-hoc alternative. See the expanded version (Yun and Azizan, 2025) for details on the EUQ modules.

Deep Ensembles. Lakshminarayanan et al. (2017) introduce a simple and high-performing non-Bayesian approach for epistemic uncertainty quantification. Deep Ensemble involves training an ensemble of M networks, e.g., $M = 5$, with identical architectures but different random initializations. At runtime, all M networks make a prediction. The epistemic uncertainty is then quantified by the variance in their outputs. If the models disagree, the uncertainty is high. While this method is effective at producing high-quality epistemic uncertainty estimates for OoD inputs, it requires the training and inference of M -number of networks, making it a computationally expensive procedure.

SCOD. Sharma et al. (2021) propose Sketching Curvature for OoD Detection (SCOD), a model architecture-agnostic method that equips a single, pre-trained network with an uncertainty score post-hoc. It builds on the Laplace approximation (MacKay, 1992), which uses the curvature of the loss landscape (characterized by the Fisher information matrix) to estimate epistemic uncertainty. SCOD operates in two phases. Offline, it computes and stores a tractable, low-rank approximation (a ‘‘sketch’’) of the training data’s Fisher matrix. Online, it compares a new input’s local curvature to the known curvature of the training data. A significant mismatch results in a high uncertainty score. Unlike Deep Ensemble, SCOD only needs a single pre-trained model, making it an efficient option for real-time deployment. Sharma et al. (2021) show that SCOD’s OoD-detection ability often matches or exceeds Deep Ensemble’s, with favorable runtime/AUROC Pareto efficiency.

4. ATOM-CBF: Adaptive-To-OoD-Measurement Control Barrier Function

The concepts reviewed thus far highlight our central challenge. We aim to design a controller that ensures safety in the sense of control invariance (Def. 1) for systems relying on an imperfect DNN-based perception module \hat{q} in the presence of OoD measurements. The MR-CBF framework (Sec. 3.2) provides a path, but its reliance on a known, static error bound $\epsilon(y)$ makes it vulnerable to OoD data, where unmodeled epistemic uncertainty $\text{Unc}(y)$ can cause the true perception error to violate this bound. This motivates our problem: *to design a safe control framework that adapts its robustness by explicitly incorporating the measured epistemic uncertainty, without access to ground-truth states or any information about the OoD distribution.* We formalize this as follows:

Problem 1 Consider the system dynamics (1) with an initial state $x(0) \in \mathcal{C}$, sensor map p , and learned perception map \hat{q} in (4). Let $h : \mathbb{R}^n \rightarrow \mathbb{R}$ be a continuously differentiable constraint function defining the safe set \mathcal{C} , and let $\text{Unc} : \mathbb{R}^l \rightarrow \mathbb{R}_+$ be an EUQ module that provides an estimate of the epistemic uncertainty for a given measurement y . Design a safe control framework, consisting of: (1) an adaptive perception error margin, $\epsilon_{\text{adapt}}(y)$, as a function of the epistemic uncertainty score $\text{Unc}(y)$, and (2) a safe control law $u_{\text{safe}} = k(\hat{x}, \epsilon_{\text{adapt}}(y))$ such that for every $x(0) \in \mathcal{C}$, $x(t) \in \mathcal{C}$ for all $t \geq 0$.

4.1. OoD-Aware Adaptive Perception Error Margin

This section details the process for computing our *OoD-aware adaptive perception error margin*. This bound is a critical component that will enable our downstream safety filter to adjust its conservatism in real-time, providing adaptive safety even when encountering OoD measurements.

1. **Filtered Calibration Set.** We start with an initial calibration dataset, $\mathcal{D}_{\text{cal}} = \{(y_i, x_i)\}_{i=1}^N$, where y_i is a measurement, x_i is the corresponding ground-truth state, and \mathcal{D}_{cal} is drawn from the identical distribution as the training dataset. To create a stable set, we first compute the uncertainty scores for the calibration data, $S_{\text{cal}} = \{\text{Unc}(y_i)\}_{i=1}^N$, and compute its mean μ_{unc} . We then introduce a user-defined filter hyperparameter $\gamma > 0$, which sets an absolute tolerance around the mean. The *filtered ID set*, $\mathcal{D}_{\text{filtered}}$, is then defined by removing statistical outliers:

$$\mathcal{D}_{\text{filtered}} \triangleq \{(y_i, x_i) \in \mathcal{D}_{\text{cal}} : |\text{Unc}(y_i) - \mu_{\text{unc}}| \leq \gamma\}. \quad (6)$$

2. **Base Error Ratio.** We define the *base error ratio*, $\varphi_{\text{cal}} \in \mathbb{R}_+^n$, where each j -th element represents the worst-case ratio of the element-wise true estimation error to the measured epistemic uncertainty, computed over the filtered ID set:

$$\varphi_{\text{cal},j} \triangleq \max_{(y_i, x_i) \in \mathcal{D}_{\text{filtered}}} \left(\frac{|\hat{q}_j(y_i) - x_{i,j}|}{\text{Unc}(y_i)} \right), \quad \forall j \in \{1, \dots, n\}, \quad (7)$$

where $\hat{q}_j(y_i)$ and $x_{i,j}$ are the j -th components of the estimated and true state vectors, respectively. This definition of φ_{cal} is inspired by the method of conformalizing scalar uncertainty estimates (Angelopoulos and Bates, 2022), where we effectively set the risk level to be the worst-case. A detailed discussion is provided in the expanded version (Yun and Azizan, 2025).

3. **Adaptive Perception Error Margin.** For any new measurement y encountered during deployment, we compute its epistemic uncertainty $\text{Unc}(y)$. Using this, we define the adaptive perception error margin, $\epsilon_{\text{adapt}}(y) : \mathbb{R}^l \rightarrow \mathbb{R}_+$:

$$\epsilon_{\text{adapt}}(y) \triangleq \|\varphi_{\text{cal}} \text{Unc}(y)\|_2. \quad (8)$$

The adaptive perception error margin, ϵ_{adapt} is the core mechanism of our method. If the measurement y is OoD, the EUQ module will output a high uncertainty score, $\text{Unc}(y)$. This dynamically and proportionally increases the assumed error bound ϵ_{adapt} , forcing the downstream safety filter to be more conservative to account for the high uncertainty of the OoD measurement.

Remark 5 *The filtering procedure in (6) is a stabilization heuristic to prevent φ_{cal} from being skewed by outliers, i.e., data points with anomalously low uncertainty ($\text{Unc}(y_i) \approx 0$) but non-trivial perception error. This step prevents the base error ratio (7) from becoming arbitrarily large and rendering the downstream safety filter overly conservative. Sec. 5.1 demonstrates this empirically.*

4.2. Adaptive Safe Control against OoD Measurements

Having defined the OoD-aware adaptive perception error margin $\epsilon_{\text{adapt}}(y)$ in Sec. 4.1, we now address the second part of Problem 1: constructing the safe control law. Our approach is to integrate this adaptive margin directly into the MR-CBF framework as follows.

Definition 6 (*Adaptive-To-OoD-Measurement Control Barrier Function (ATOM-CBF)*). Let $\mathcal{C} \subset \mathbb{R}^n$ be the zero-superlevel set of a continuously differentiable function $h : \mathbb{R}^n \rightarrow \mathbb{R}$. Let $\epsilon_{\text{adapt}}(y) = \|\varphi_{\text{cal}} \cdot \text{Unc}(y)\|_2$ be the OoD-aware adaptive perception error margin, given an OoD measurement y . Here, φ_{cal} is the base error ratio from (7) and $\text{Unc}(y)$ is the output of an epistemic uncertainty quantification (EUQ) module. The function h is an Adaptive-to-OoD-Measurement Control Barrier Function (ATOM-CBF) for system (1) on \mathcal{C} if there exists an extended class \mathcal{K}_∞ function κ such that

$$\sup_{u \in \mathbb{R}^m} \left\{ \mathcal{L}_f h(\hat{x}) + \mathcal{L}_g h(\hat{x})u - \epsilon_{\text{adapt}}(y) (\mathbb{L}_{\mathcal{L}_f h} + \mathbb{L}_{\kappa \circ h} + \mathbb{L}_{\mathcal{L}_g h} \|u\|_2) \right\} \geq -\kappa(h(\hat{x})). \quad (9)$$

Compared to (5), (9) does not have the robustness terms $a(y)$ and $b(y)$ fixed with a static $\epsilon(y)$. Instead, they adapt based on the online estimate of the epistemic uncertainty, providing an adaptive robustness buffer that scales with the measured epistemic uncertainty. We now introduce our optimization-based safety filter as follows:

$$\begin{aligned} u_{\text{safe}} = \arg \min_{u \in \mathbb{R}^m} & \quad \frac{1}{2} \|u - u_{\text{nom}}\|_2^2 \\ \text{s.t. } & \mathcal{L}_f h(\hat{x}) + \mathcal{L}_g h(\hat{x})u - \epsilon_{\text{adapt}}(y) (\mathbb{L}_{\mathcal{L}_f h} + \mathbb{L}_{\kappa \circ h} + \mathbb{L}_{\mathcal{L}_g h} \|u\|_2) \geq -\kappa(h(\hat{x})), \end{aligned} \quad (10)$$

where $\hat{x} = \hat{q}(y)$, and u_{nom} is a potentially unsafe control input from a nominal controller, e.g., a goal-reaching controller. The constraint in (10) is non-smooth, making the optimization problem a second-order cone program (SOCP), which is solved online. To ensure constraint feasibility in practice, we follow the approach in Dean et al. (2021) and introduce a slack variable, δ , to the constraint, which is heavily penalized. Details are in the expanded version (Yun and Azizan, 2025).

5. Experimental Results

We test ATOM-CBF on two testbeds: a 2-dimensional FITenth vehicle with LiDAR scans (Sec. 5.1) and a 3-dimensional quadruped robot with RGB camera images (Sec. 5.2). In both experiments, the perception modules are DNNs trained to detect a single, static obstacle. While the experimental details differ, both experiments share a common foundation.

System Dynamics. We model both systems using the 2D unicycle dynamics with respect to a static obstacle:

$$\dot{x} = \begin{bmatrix} \dot{d} \\ \dot{\alpha} \end{bmatrix} = \underbrace{\mathbf{0}_{2 \times 1}}_{f(x)} + \underbrace{\begin{bmatrix} -\cos(\alpha) & 0 \\ -\sin(\alpha)/d & 1 \end{bmatrix}}_{g(x)} \underbrace{\begin{bmatrix} v \\ \omega \end{bmatrix}}_u, \quad (11)$$

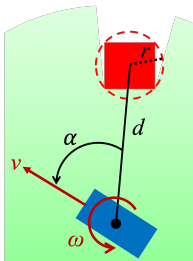


Figure 2: F1/10.

where the state $x = [d, \alpha]^\top$ consists of distance d to a static obstacle and relative heading angle α with respect to the obstacle. The control inputs are the longitudinal velocity v and yaw rate ω . This reduced-order model (ROM) abstracts away the low-level control of the robot to focus on high-level navigation. Both experiments consider various shapes of obstacles: F1Tenth experiment uses circle, triangle, square, and star obstacles, and quadruped experiment uses sphere and cube obstacles. The unsafe region is defined by the minimum enclosing circle of radius r of the obstacle in the 2-dimensional navigation space, irrespective of the obstacle geometry, as shown in Fig. 2.

Calibration and Base Error Ratio. The calibration procedure from Sec. 4.1 with $\gamma = \sigma_{\text{unc}}$, i.e., standard deviation of S_{cal} , is used for both experiments, though with different $\mathcal{D}_{\text{filtered}}$ datasets. Full statistics are provided in the expanded version (Yun and Azizan, 2025).

Safety Objective and Filters. For both experiments, the safety objective is to avoid collision with the obstacle. For this, we employ a state-based cone CBF, inspired by Collision Cone CBFs (Thontepu et al., 2022; Tayal and Kolathaya, 2023; Tayal et al., 2024). This CBF ensures that the vehicle does not point toward any detected obstacle: $h(\hat{x}) = |\hat{\alpha}| - \sin^{-1}(r/\hat{d})$, where the radius r is assumed to be known and $\hat{d} > r$ is enforced for all timesteps. Using this CBF, we construct and compare the following three safety filters:

1. **CBF-QP:** Baseline; a standard CBF-QP with constraint (3), as in Ames et al. (2017).
 2. **ATOM-CBF (SCOD):** Our SOCP adaptive filter (10), with SCOD as the EUQ module.
 3. **ATOM-CBF (Deep):** Our SOCP adaptive filter (10), with Deep Ensemble as the EUQ module.
- Note that for each experiment, all safety filters receive their state estimate $\hat{x} = [\hat{d}, \hat{\alpha}]^\top$ from the identical perception module trained on in-distribution (ID) data.

5.1. 2D Experiment: F1Tenth Vehicle Control with LiDAR Scans

Table 1: Simulation results for F1Tenth vehicle control (1,000 trajectories each).^a

Safety Filter	ID (Circle)		OoD (Square, Triangle, Star)	
	CBF-QP	CBF-QP	ATOM-CBF (SCOD)	ATOM-CBF (Deep)
Reach	100%	63.60%	96.10%	33.70%
Deadlock	0.00%	18.40%	3.90%	66.30%
Collision	0.00%	18.00%	0.00%	0.00%
d -Coverage	—	—	20.58%	70.27%
α -Coverage	—	—	54.35%	99.99%
AUROC	—	—	0.9563	0.9971

^a See the expanded version (Yun and Azizan, 2025) for details on coverages and AUROC.

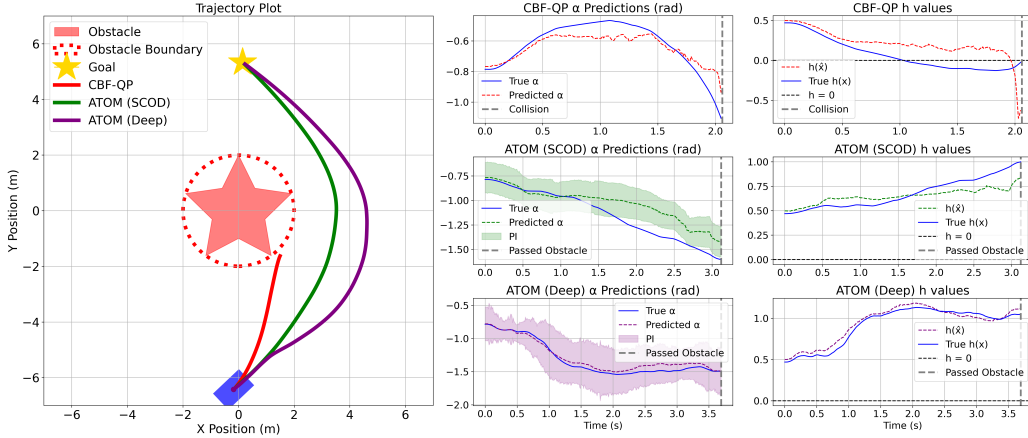


Figure 3: F1Tenth vehicle experiment with a star obstacle. All trajectories start with an identical initial condition and OoD obstacle, comparing three controller variants: CBF-QP (red), ATOM-CBF with SCOD (green), ATOM-CBF with Deep Ensemble (purple). (Left) Trajectory plot. (Middle) Time plots of true α (blue) vs. predicted $\hat{\alpha}$ and its prediction interval (PI). (Right) Time plots of true $h(x)$ (blue) vs. estimated $h(\hat{x})$. Perception and safety filters are engaged until the vehicle passes the obstacle, at which point the nominal controller resumes control using the ground-truth state.

Environment and Perception. We employ the F1Tenth Gym platform (O’Kelly et al., 2020), where the sensor map p models a 1,080-dimensional 2D LiDAR scan with 360° field-of-view (FOV). The perception map is a convolutional neural network (CNN) that takes this 1,080-dimensional LiDAR measurement and outputs the estimated state, $[\hat{d}, \hat{\alpha}]^\top$.

Nominal Objective. The nominal PD controller directs the vehicle straight to a goal behind the obstacle using perfect global state information, $[x, y, \theta]^\top$, without accounting for the obstacle. This forces the safety filter to intervene.

ID vs. OoD. The perception module was trained on ID data of small (0.1 - 0.5 m radius) *circle* obstacles. The OoD challenge introduces geometrically distinct (*square, triangle, star*) and much larger (1.5 - 2.0 m side-length) obstacles. See Fig. 1 for the significant difference in obstacles.

Results and Analysis. Table 1 summarizes the results. The CBF-QP baseline, while 100% successful on ID data, collided in 18% of OoD trials. In contrast, both ATOM-CBF variants achieve a 0% collision rate, successfully adapting to OoD measurements. However, Table 1 reveals a key performance trade-off. ATOM-CBF (Deep) is overly conservative, leading to a high deadlock rate (66.30%), whereas ATOM-CBF (SCOD) achieves safety with a 96.10% reach rate. This stems from Deep Ensemble’s large $\text{Unc}(y)$ jump for OoD data compared to ID data, producing a higher AUROC, larger $\epsilon_{\text{adapt}}(y)$, and greater robustness buffer. This over-conservatism is reflected in its 99.99% α -coverage and wide PI in Fig. 3. While ATOM-CBF (Deep) trajectory (purple) takes a much wider path, ATOM-CBF (SCOD) trajectory (green) is tighter with a smaller buffer. Note that high coverage is not our goal, but we include it to illustrate the large, conservative bounds that cause the safety filter to deadlock. Additional details are in the expanded version (Yun and Azizan, 2025).

The success of ATOM-CBF (SCOD) hinges on the filtering heuristic (Sec. 4.1), which is necessary to filter statistical outliers that cause the base error ratio, φ_{cal} , to become unreasonably large. Table 2 validates this by ablating the filter width γ . As γ increases to $5 \cdot \sigma_{\text{unc}}$, it includes these outliers, causing φ_{cal} to jump to the unfiltered value, i.e., when $\gamma = \infty$. This increased φ_{cal} results in

over-conservatism, causing performance to drop drastically. This shows γ is a tunable parameter for adjusting the desired conservatism. Our chosen value, $\gamma = \sigma_{\text{unc}}$, proves to be an effective heuristic.

Table 2: Ablation study on the hyperparameter γ for ATOM-CBF (SCOD) (1,000 trajectories each).

SCOD: Filtering & Calibration		ATOM-CBF (SCOD): F1Tenth Result				
γ	$\varphi_{\text{cal}}([d, \alpha])$	Reach	Deadlock	Collision	d -coverage	α -coverage
σ_{unc}	[3.690e-2, 1.777e-2]	96.10%	3.90%	0.00%	20.58%	54.35%
$2 \cdot \sigma_{\text{unc}}$	[3.959e-2, 1.963e-2]	92.50%	7.50%	0.00%	24.51%	51.68%
$4 \cdot \sigma_{\text{unc}}$	[3.961e-2, 1.963e-2]	90.30%	9.70%	0.00%	26.81%	56.48%
$5 \cdot \sigma_{\text{unc}} (\approx \infty)$	[8.574e-2, 2.260e-2]	28.30%	71.70%	0.00%	57.25%	79.75%

5.2. 3D Experiment: Quadruped Control with RGB Camera Images

Environment and Perception. Here, we use a Unitree Go2 robot in a 3D MuJoCo environment. The sensor map p models a 1280×720 (58° vertical FOV) RGB feed from the quadruped’s fixed-height head camera. The perception map is a CNN that outputs estimated state, $[\hat{d}, \hat{\alpha}]^\top$.

Nominal Objective. The same nominal PD controller now acts as an adversarial, directing the quadruped to cause a collision, as shown in Fig. 4. In this experiment, there is no goal point to reach.



Figure 4: Quadruped crash (OoD). OoD scenery. Fig. 4 shows CBF-QP crashing in OoD.

ID vs. OoD. The perception module was trained on ID data of high-contrast scenes with a sphere obstacle. The OoD challenge simulates dense fog by using high ambient and low diffuse light, creating a “washed-out” effect, i.e., a low-contrast environment where the obstacle and background are difficult to distinguish. Furthermore, the obstacle is a cube with side length 1.0 m. See Fig. 1 for the visual difference in ID vs.

Results and Analysis. We evaluated each safety filter over 100 trials. In the ID setting (high-contrast, sphere), the baseline CBF-QP collided in only 2% of trials. However, in the OoD challenge (low-contrast, cube), the CBF-QP collided in 97% of trajectories. In stark contrast, both ATOM-CBF variants achieved a 0% collision rate in the OoD setting, demonstrating their ability to adapt to the challenging measurements and maintain safety. AUROC is above 0.99 for both EUQs.

6. Conclusion and Future Work

In this work, we propose ATOM-CBF, a novel framework for safe perception-based control under OoD measurements. It features an adaptive error margin that scales with epistemic uncertainty, integrated into a safety filter that dynamically adjusts its conservatism. We empirically validated ATOM-CBF in two distinct high-fidelity robotic environments, demonstrating that it maintains safety in challenging OoD scenarios. The efficacy of our approach is linked to the performance of the underlying EUQ module, and the safety assurances are contingent on the EUQ module’s capacity to reliably detect novel OoD inputs. Our experiments further highlight a trade-off: the choice of EUQ module and filtering hyperparameter dictates the controller’s conservatism and task performance. Future work includes incorporating online updates to the base error ratio using adaptive conformal prediction methods (Zhou et al., 2024) and deploying ATOM-CBF in the real world.

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References

- Aaron D. Ames, Xiangru Xu, Jessy W. Grizzle, and Paulo Tabuada. Control barrier function based quadratic programs for safety critical systems. *IEEE Transactions on Automatic Control*, 62(8): 3861–3876, 2017.
- Aaron D Ames, Samuel Coogan, Magnus Egerstedt, Gennaro Notomista, Koushil Sreenath, and Paulo Tabuada. Control barrier functions: Theory and applications. In *European control conference*, 2019.
- Anastasios N. Angelopoulos and Stephen Bates. A gentle introduction to conformal prediction and distribution-free uncertainty quantification, 2022.
- Ryan M. Bena, Gilbert Bahati, Blake Werner, Ryan K. Cosner, Lizhi Yang, and Aaron D. Ames. Geometry-aware predictive safety filters on humanoids: From poisson safety functions to CBF constrained MPC. In *2025 IEEE-RAS 24th International Conference on Humanoid Robots (Humanoids)*, pages 1–8, 2025.
- Robin A Brown, Edward Schmerling, Navid Azizan, and Marco Pavone. A unified view of SDP-based neural network verification through completely positive programming. In *International conference on artificial intelligence and statistics*, pages 9334–9355. PMLR, 2022.
- Fernando Castañeda, Haruki Nishimura, Rowan Thomas McAllister, Koushil Sreenath, and Adrien Gaidon. In-distribution barrier functions: Self-supervised policy filters that avoid out-of-distribution states. In *Proceedings of The 5th Annual Learning for Dynamics and Control Conference*, volume 211 of *Proceedings of Machine Learning Research*, pages 286–299. PMLR, 2023.
- Kaustav Chakraborty, Aryaman Gupta, and Somil Bansal. Enhancing safety and robustness of vision-based controllers via reachability analysis, 2024.
- Jose Leopoldo Contreras, Ola Shorinwa, and Mac Schwager. Safe, out-of-distribution-adaptive MPC with conformalized neural network ensembles, 2025.
- Ryan K. Cosner, Ivan Dario Jimenez Rodriguez, Tamás G. Molnár, Wyatt Ubellacker, Yisong Yue, A. Ames, and Katherine L. Bouman. Self-supervised online learning for safety-critical control using stereo vision. *2022 International Conference on Robotics and Automation (ICRA)*, pages 11487–11493, 2022.
- Charles Dawson, Bethany Lowenkamp, Dylan Goff, and Chuchu Fan. Learning safe, generalizable perception-based hybrid control with certificates. *IEEE Robotics and Automation Letters*, 7(2): 1904–1911, 2022.

- Sarah Dean and Benjamin Recht. Certainty equivalent perception-based control. In *Proceedings of the 3rd Conference on Learning for Dynamics and Control*, volume 144 of *Proceedings of Machine Learning Research*, pages 399–411. PMLR, 07 – 08 June 2021.
- Sarah Dean, Andrew Taylor, Ryan Cosner, Benjamin Recht, and Aaron Ames. Guaranteeing safety of learned perception modules via measurement-robust control barrier functions. In *Proceedings of the 2020 Conference on Robot Learning*, Proceedings of Machine Learning Research. PMLR, 2021.
- Anushri Dixit, Zhiting Mei, Meghan Booker, Mariko Storey-Matsutani, Allen Z. Ren, and Anirudha Majumdar. Perceive with confidence: Statistical safety assurances for navigation with learning-based perception. In *Proceedings of The 8th Conference on Robot Learning*, Proceedings of Machine Learning Research, pages 2517–2541. PMLR, 2025.
- Tairan He, Chong Zhang, Wenli Xiao, Guanqi He, Changliu Liu, and Guanya Shi. Agile but safe: Learning collision-free high-speed legged locomotion. In *Robotics: Science and Systems (RSS)*, 2024.
- Dan Hendrycks, Norman Mu, Ekin Dogus Cubuk, Barret Zoph, Justin Gilmer, and Balaji Lakshminarayanan. Augmix: A simple method to improve robustness and uncertainty under data shift. In *International Conference on Learning Representations*, 2020.
- Chiao Hsieh, Yangge Li, Dawei Sun, Keyur Joshi, Sasa Misailovic, and Sayan Mitra. Verifying controllers with vision-based perception using safe approximate abstractions. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, 41(11):4205–4216, 2022.
- Huang Huang, Satvik Sharma, Antonio Loquercio, Anastasios Angelopoulos, Ken Goldberg, and Jitendra Malik. Conformal policy learning for sensorimotor control under distribution shifts. In *2024 IEEE International Conference on Robotics and Automation (ICRA)*, pages 16285–16291, 2024.
- Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell. Simple and scalable predictive uncertainty estimation using deep ensembles. In *Advances in Neural Information Processing Systems*, pages 6402–6413, 2017.
- Albert Lin, Shuang Peng, and Somil Bansal. One filter to deploy them all: Robust safety for quadrupedal navigation in unknown environments, 2024.
- Changliu Liu and Masayoshi Tomizuka. Control in a safe set: Addressing safety in human-robot interactions. In *Dynamic Systems and Control Conference*, 2014.
- B. T. Lopez and J.-E. Slotine. Unmatched control barrier functions: Certainty equivalence adaptive safety. In *American Control Conference*, pages 3662–3668. IEEE, 2023.
- David John Cameron MacKay. A practical bayesian framework for backpropagation networks. *Neural Computation*, 4:448–472, 1992.
- Anirudha Majumdar and Maxwell Goldstein. Pac-bayes control: Synthesizing controllers that provably generalize to novel environments. In *Proceedings of The 2nd Conference on Robot Learning*, volume 87 of *Proceedings of Machine Learning Research*, pages 293–305. PMLR, 29–31 Oct 2018.

- Anirudha Majumdar, Alec Farid, and Anoopkumar Sonar. Pac-bayes control: learning policies that provably generalize to novel environments. *The International Journal of Robotics Research*, 40 (2-3):574–593, 2021.
- Matthew O’Kelly, Hongrui Zheng, Dhruv Karthik, and Rahul Mangharam. Fltenth: An open-source evaluation environment for continuous control and reinforcement learning. In *NeurIPS 2019 Competition and Demonstration Track*, pages 77–89. PMLR, 2020.
- Young-Jin Park, Carson Sobolewski, and Navid Azizan. Uncertainty quantification in detection transformers: Object-level calibration and image-level uncertainty. *arXiv preprint arXiv:2412.01782*, 2024a.
- Young-Jin Park, Hao Wang, Shervin Ardeshtir, and Navid Azizan. Quantifying representation reliability in self-supervised learning models. In *Proceedings of the Fortieth Conference on Uncertainty in Artificial Intelligence*, pages 2835–2860, 2024b.
- Young-Jin Park, Kristjan Greenewald, Kaveh Alim, Hao Wang, and Navid Azizan. Know what you don’t know: Uncertainty calibration of process reward models. *arXiv preprint arXiv:2506.09338*, 2025.
- Alfredo Reichlin, Giovanni Luca Marchetti, Hang Yin, Ali Ghadirzadeh, and Danica Kragic. Back to the manifold: Recovering from out-of-distribution states. In *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 8660–8666, 2022.
- Charles Richter and Nicholas Roy. Safe visual navigation via deep learning and novelty detection. In *Proceedings of Robotics: Science and Systems*, Cambridge, Massachusetts, July 2017.
- Junwon Seo, Kensuke Nakamura, and Andrea Bajcsy. Uncertainty-aware latent safety filters for avoiding out-of-distribution failures, 2025.
- Apoorva Sharma, Navid Azizan, and Marco Pavone. Sketching curvature for efficient out-of-distribution detection for deep neural networks. In *Proceedings of the Thirty-Seventh Conference on Uncertainty in Artificial Intelligence*, Proceedings of Machine Learning Research, pages 1958–1967. PMLR, 2021.
- Manan Tayal and Shishir Kolathaya. Control barrier functions in dynamic uavs for kinematic obstacle avoidance: A collision cone approach. *arXiv preprint arXiv:2303.15871*, 2023.
- Manan Tayal, Bhavya Giri Goswami, Karthik Rajgopal, Rajpal Singh, Tejas Rao, Jishnu Keshavan, Pushpak Jagtap, and Shishir Kolathaya. A collision cone approach for control barrier functions. 2024.
- Phani Thontepu, Bhavya Giri Goswami, Neelaksh Singh, Shyamsundar PI, Suresh Sundaram, Vaibhav Katewa, et al. Control barrier functions in ugvs for kinematic obstacle avoidance: A collision cone approach. *arXiv preprint arXiv:2209.11524*, 2022.
- Josh Tobin, Rachel Fong, Alex Ray, Jonas Schneider, Wojciech Zaremba, and Pieter Abbeel. Domain randomization for transferring deep neural networks from simulation to the real world. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, page 23–30. IEEE Press, 2017.

- Tara Toufighi, Minh Bui, Rakesh Shrestha, and Mo Chen. Decision boundary learning for safe vision-based navigation via Hamilton-Jacobi reachability analysis and support vector machine. In *Proceedings of the 6th Annual Learning for Dynamics and Control Conference*, volume 242 of *Proceedings of Machine Learning Research*, pages 440–452. PMLR, 15–17 Jul 2024.
- Tianhao Wei and Changliu Liu. Safe control algorithms using energy functions: A unified framework, benchmark, and new directions. In *2019 IEEE 58th Conference on Decision and Control (CDC)*, pages 238–243. IEEE, 2019.
- Tianhao Wei, Hanjiang Hu, Luca Marzari, Kai S. Yun, Peizhi Niu, Xusheng Luo, and Changliu Liu. Modelverification.jl: A comprehensive toolbox for formally verifying deep neural networks. In *Computer Aided Verification*, pages 395–408. Springer Nature Switzerland, 2025.
- Lorenz Wellhausen, René Ranftl, and Marco Hutter. Safe robot navigation via multi-modal anomaly detection. *IEEE Robotics and Automation Letters*, 5(2):1326–1333, 2020.
- Wei Xiao, Calin Belta, and Christos G Cassandras. Adaptive control barrier functions. *IEEE Transactions on Automatic Control*, 67(5):2267–2281, 2021.
- Shuo Yang, George J. Pappas, Rahul Mangharam, and Lars Lindemann. Safe perception-based control under stochastic sensor uncertainty using conformal prediction. In *2023 62nd IEEE Conference on Decision and Control (CDC)*, 2023.
- Kai S. Yun and Navid Azizan. ATOM-CBF: Adaptive safe perception-based control under out-of-distribution measurements. 2025. URL <https://arxiv.org/abs/2511.08741>.
- Kai S. Yun, Rui Chen, Chase Dunaway, John M. Dolan, and Changliu Liu. Safe control of quadruped in varying dynamics via safety index adaptation. In *2025 IEEE International Conference on Robotics and Automation (ICRA)*, pages 7771–7777, 2025.
- Hao Zhou, Yanze Zhang, and Wenhao Luo. Safety-critical control with uncertainty quantification using adaptive conformal prediction. In *2024 American Control Conference (ACC)*, pages 574–580, 2024.