Capability-Aware Heterogeneous Control Barrier Functions for Decentralized Multi-Robot Safe Navigation

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***Abstract*— Safe navigation for multi-robot systems requires enforcing safety without sacrificing task efficiency under decentralized decision-making. Existing decentralized methods often assume robot homogeneity, making shared safety requirements difficult to enforce consistently across heterogeneous agents with structurally different dynamics, which can lead to avoidance obligations that are not physically realizable for some robots and consequently cause safety violations or overly conservative behavior. We propose the *Capability-Aware Heterogeneous Control Barrier Function* (*CA-HCBF*), a decentralized framework for consistent safety enforcement and capability-aware coordination across heterogeneous robot models. CA-HCBF maps holonomic and nonholonomic robots into a common second-order operational space, enabling a shared pairwise CBF formulation while retaining their model-specific motion responses and admissible control constraints. We further introduce a support-function-based directional capability measure to allocate pairwise collision-avoidance responsibility according to each robot's realizable motion capability. A feasibility-aware clipping mechanism restricts these allocations to individually achievable ranges, reducing physically unrealizable safety assignments in dense decentralized interactions. Simulations with up to 30 heterogeneous robots and a five-robot hardware experiment demonstrate improved safety and task efficiency over representative baselines. [Extended Version]**

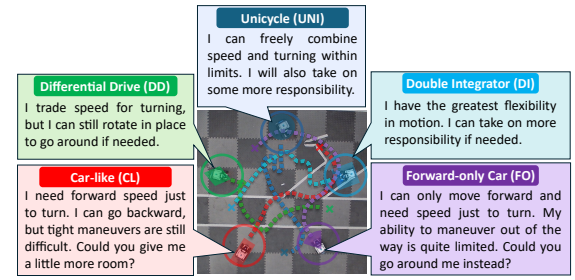
I. Introduction

With recent advances in robotics, multi-robot systems (MRS) are increasingly used for collaborative tasks such as exploration, search-and-rescue, autonomous delivery, and warehouse automation [1]–[4]. As robot density increases, safe navigation becomes more challenging, since frequent interactions increase collision risk while overly conservative avoidance can degrade team efficiency.

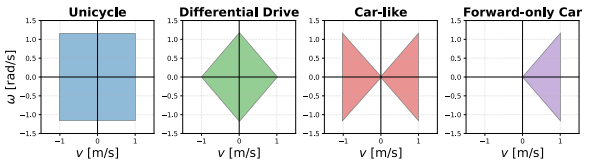
Control barrier functions (CBFs) [6], [7] provide a principled framework for enforcing safety by modifying nominal control commands through a quadratic program (QP) to maintain forward invariance of a prescribed safe set [8]. CBF-based navigation can be implemented in either centralized or decentralized forms. While centralized formulations provide globally coordinated safety decisions, they scale poorly with team size. Decentralized formulations scale more naturally, but reciprocal pairwise safety constraints require the avoidance effort to be distributed across interacting robots, making responsibility allocation important for both safety and feasibility [9]. Existing responsibility-allocation approaches either assume homogeneous dynamics [10] or consider parametric heterogeneity within a shared model class [11].

Despite this progress, safe and efficient decentralized navigation for structurally heterogeneous robot teams remains an open challenge. Robots may differ not only in parameters such as speed limits or footprint, but also in their underlying kinematic constraints, relative degrees, and admissible control sets, as illustrated in Fig. 1 (a). Consequently, the same collision-avoidance requirement may demand substantially different control effort across robot models, and uniform responsibility allocation may assign physically unrealizable avoidance effort to constrained robots while underutilizing more maneuverable ones. Treating neighboring robots as worst-case dynamic obstacles provides one conservative alternative [12], but sacrifices reciprocal cooperation. Moreover, restricted control authority can make local decentralized QPs particularly susceptible to infeasibility when multiple pairwise constraints become simultaneously active [13]. This capability mismatch is particularly important in tightly coupled multi-robot settings, where safe physical coordination requires robots with different maneuvering constraints to negotiate shared space.

These observations motivate two requirements for decentralized safety in heterogeneous robot teams: (i) a unified safety formulation that can be applied consistently across structurally different robot dynamics, and (ii) a responsibility allocation mechanism that distributes avoidance effort according to each robot's realizable directional motion capability while limiting physically unrealizable assignments.



(a)



UNI	DD	CL	FO
$\lvert v\rvert \le v_{\max}$, $\lvert\omega\rvert \le \omega_{\max}$	$\frac{\lvert v\rvert}{v_{\max}} + \frac{\lvert\omega\rvert}{\omega_{\max}} \le 1$	$\lvert\omega\rvert \le \frac{\lvert v\rvert \tan(\psi_{\max})}{l}$	CL with $\lvert v\rvert \ge 0$

(b)

Fig. 1: (a) Five mobile robots with heterogeneous kinematic classes (DI, UNI, DD, CL, FO) navigate toward individual goals. Each robot's statement reflects its directional motion capability, ranging from the holonomic DI to the more kinematically constrained CL and FO, motivating the capability-aware responsibility allocation in Section II. **(b)** Velocity-level feasible sets $\mathcal{V}_i$ in the (v, ω) space and their analytical definitions for the four nonholonomic kinematic classes [5].

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To meet these requirements, we propose the *Capability-Aware Heterogeneous Control Barrier Function* (*CA-HCBF*), a decentralized framework for heterogeneous multi-robot safety. CA-HCBF introduces (1) a unified second-order CBF formulation for holonomic and nonholonomic mobile robot models, (2) a support-function-based directional capability metric with feasibility-aware responsibility allocation, and (3) extensive simulation and hardware validation demonstrating improved task completion, fewer safety violations, and enhanced decentralized feasibility over representative baselines.

II. Capability-Aware Decentralized CBF for Heterogeneous Multi-Robot Systems

We consider a heterogeneous team of N mobile robots operating in a shared 2D workspace. Each robot i is associated with a model $c_i \in \mathcal{C}$, where the models may differ in their kinematic constraints, actuation limits, and admissible control sets. The dynamics of robot i are given by $\dot{\mathbf{x}}_i = f_{c_i}(\mathbf{x}_i) + g_{c_i}(\mathbf{x}_i)\mathbf{u}_i$, with $\mathbf{u}_i \in \mathcal{U}_{c_i}(\mathbf{x}_i)$. We focus on robot models that admit a common second-order operational-space representation, introduced in Sec. II-A. Our objective is to construct decentralized controls that maintain pairwise collision avoidance while accounting for differences in the motion capabilities of interacting robots. For notational simplicity, we omit the explicit model index c_i below.

A. Unified Operational-Space Safety Formulation

Different robot models describe their motion through model-specific state and control coordinates, making it difficult to impose a common physical safety constraint directly. We therefore use a reference-point mapping [5] to represent heterogeneous robot models in a shared Cartesian operational space, where relative motion and safety interactions have a consistent physical interpretation across models.

In this work, we consider robot models that admit such a reference-point operational representation, including five representative mobile-robot models: the holonomic Double Integrator (DI) and the nonholonomic Unicycle (UNI), Differential Drive (DD), Car-Like (CL), and Forward-Only (FO), as illustrated in Fig. 1. For the nonholonomic models, we define a reference point located a distance $x_{r,i} > 0$ along the robot heading[1],

$$\mathbf{p}_i = \begin{bmatrix} x_i + x_{r,i}\cos\phi_i \\ y_i + x_{r,i}\sin\phi_i \end{bmatrix}. \tag{1}$$

For the nonholonomic models, let $\boldsymbol{\nu}_i = [v_i, \omega_i]^\top$ denote the body velocity and $\mathbf{u}_i := \dot{\boldsymbol{\nu}}_i$ the generalized acceleration, with $\mathbf{u}_i \in \mathcal{U}_i^{\mathrm{acc}}(\mathbf{x}_i)$ capturing the model-specific kinematic and actuation limits. Differentiating the reference-point dynamics under generalized acceleration control yields the common second-order form

$$\ddot{\mathbf{p}}_i = \boldsymbol{\eta}_i(\mathbf{x}_i) + G_i(\mathbf{x}_i)\mathbf{u}_i, \tag{2}$$

[1]For DI, $x_{r,i} = 0$, $G_i = I_2$, and $\boldsymbol{\eta}_i = \mathbf{0}$.

where $\boldsymbol{\eta}_i$ denotes the state-dependent drift and G_i maps the model-specific control input into operational-space acceleration. For the nonholonomic models, $G_i = [\,(\cos\phi_i, \sin\phi_i)^\top,\ x_{r,i}(-\sin\phi_i, \cos\phi_i)^\top\,]$, while the DI corresponds to $G_i = I_2$ and $\boldsymbol{\eta}_i = \mathbf{0}$. Thus, relative motion and safety have a common physical interpretation across robot models, while their model-specific motion responses and admissible control constraints are retained through $\boldsymbol{\eta}_i$, G_i, and $\mathcal{U}_i^{\mathrm{acc}}$.

For each pair (i, j), let $\Delta\mathbf{p}_{ij} := \mathbf{p}_i - \mathbf{p}_j$ and define $h_{ij} := \|\Delta\mathbf{p}_{ij}\|^2 - R_{ij}^2$. Since h_{ij} has relative degree two under (2), we impose the second-order CBF condition [14], [15]

$$\ddot{h}_{ij} + (\lambda_1 + \lambda_2)\dot{h}_{ij} + \lambda_1\lambda_2 h_{ij} \geq 0. \tag{3}$$

Substituting (2) gives the coupled pairwise constraint

$$2\Delta\mathbf{p}_{ij}^\top(G_i\mathbf{u}_i - G_j\mathbf{u}_j) + 2\Delta\mathbf{p}_{ij}^\top(\boldsymbol{\eta}_i - \boldsymbol{\eta}_j) + \Upsilon_{ij} \geq 0, \tag{4}$$

where $\Upsilon_{ij} := 2\|\Delta\dot{\mathbf{p}}_{ij}\|^2 + (\lambda_1 + \lambda_2)\dot{h}_{ij} + \lambda_1\lambda_2 h_{ij}$.

The constraint (4) couples the controls of both robots. To enable decentralized execution, we introduce a responsibility parameter $\alpha_{ij} \in [0, 1]$ and assign robot i the local constraint

$$2\Delta\mathbf{p}_{ij}^\top G_i\mathbf{u}_i \geq -2\Delta\mathbf{p}_{ij}^\top\boldsymbol{\eta}_i - \alpha_{ij}\Upsilon_{ij}. \tag{5}$$

Robot j enforces the complementary share $\alpha_{ji} = 1 - \alpha_{ij}$. Summing the two local constraints recovers the coupled CBF condition (4). Hence, pairwise safety is preserved whenever the local constraints remain feasible and the standard second-order CBF initial conditions hold.

Each robot computes the admissible control closest to its nominal input while satisfying its local safety constraints and $\mathbf{u}_i \in \mathcal{U}_i^{\mathrm{acc}}(\mathbf{x}_i)$. To account for the reference-point offset and physical robot size, let r_i^{phys} denote a bounding radius of robot i and define $r_i^{\mathrm{cbf}} := x_{r,i} + r_i^{\mathrm{phys}}$ and $R_{ij} := r_i^{\mathrm{cbf}} + r_j^{\mathrm{cbf}}$. This operational-space separation provides a sufficient condition for physical collision avoidance.

B. Capability-Aware Responsibility Allocation

The decentralized decomposition above permits any complementary allocation satisfying $\alpha_{ij} + \alpha_{ji} = 1$. Equal allocation, $\alpha_{ij} = \frac{1}{2}$, implicitly assumes comparable maneuverability between the interacting robots. For heterogeneous models, however, the same assigned responsibility may require substantially different control effort. We therefore determine the allocation using the directional control capability of each robot.

1) Directional Control Capability: The controllable contribution of robot i to the pairwise separating motion is given by $2\Delta\mathbf{p}_{ij}^\top G_i\mathbf{u}_i$ in (5). We define its maximum achievable value as

$$\rho_{ij}^i := \max_{\mathbf{u}_i \in \mathcal{U}_i^{\mathrm{acc}}} 2\Delta\mathbf{p}_{ij}^\top G_i\mathbf{u}_i, \tag{6}$$

which corresponds to evaluating the support function of the operational-space admissible control set along the pairwise separation direction. Because the drift term also contributes to the pairwise CBF independently of the control input, we define the effective separating capability

$$\bar{\rho}_{ij}^i := \max\big(\rho_{ij}^i + 2\Delta\mathbf{p}_{ij}^\top\boldsymbol{\eta}_i,\ 0\big), \tag{7}$$

and analogously for robot j.

Among feasible allocations, we favor robots that can more readily recover their nominal motion. Let $\mathbf{d}_i := \dot{\mathbf{p}}_i^{\mathrm{nom}} - \dot{\mathbf{p}}_i$ and define the corresponding progress capability as $\sigma_i := \max_{\mathbf{u}_i \in \mathcal{U}_i^{\mathrm{acc}}} \mathbf{d}_i^\top G_i \mathbf{u}_i$. The progress-oriented allocation is then

$$\alpha_{ij}^{\mathrm{prog}} = \frac{\sigma_i}{\sigma_i + \sigma_j + \epsilon}, \tag{8}$$

where $\epsilon > 0$ prevents division by zero.

2) Feasibility-Aware Allocation: The progress-oriented allocation does not necessarily ensure that the assigned responsibility is individually realizable. When $\Upsilon_{ij} < 0$, the pairwise CBF requires a separating response. Using the effective capabilities in (7), the feasible responsibility interval is

$$\alpha_{\min} = \max\left(0,\, 1 - \frac{\bar{\rho}_{ij}^{j}}{-\Upsilon_{ij}}\right),\ \alpha_{\max} = \min\left(1,\, \frac{\bar{\rho}_{ij}^{i}}{-\Upsilon_{ij}}\right). \tag{9}$$

Here, $\alpha_{\max}$ is the largest share robot i can accommodate, while $\alpha_{\min}$ is the minimum share required to keep the complementary responsibility assigned to robot j individually feasible. We therefore select

$$\alpha_{ij} = \mathrm{clip}\left(\alpha_{ij}^{\mathrm{prog}}, \alpha_{\min}, \alpha_{\max}\right), \tag{10}$$

whenever $\alpha_{\min} \le \alpha_{\max}$, and use $\alpha_{ij}^{\mathrm{prog}}$ directly when $\Upsilon_{ij} \ge 0$. If $\alpha_{\min} > \alpha_{\max}$, the combined directional capability of the pair is insufficient to make both local pairwise constraints individually feasible, and we revert to equal allocation. Feasibility-aware clipping therefore removes responsibility assignments that are individually unrealizable for either robot. However, multiple simultaneously active pairwise constraints may still become jointly incompatible with the admissible control set of a single robot.

CA-HCBF. We refer to the resulting decentralized framework, combining the unified operational-space CBF with complementary capability-aware responsibility allocation and feasibility-aware clipping, as the *Capability-Aware Heterogeneous Control Barrier Function* (*CA-HCBF*).

III. Experiments

We evaluate CA-HCBF in terms of both navigation performance and practical decentralized feasibility, with particular emphasis on the effect of capability-aware responsibility allocation. Our evaluation includes (i) random start–goal simulations with up to $N = 30$ heterogeneous robots, (ii) an ablation of the proposed responsibility-allocation strategy, and (iii) a five-robot physical experiment involving all five kinematic classes.

A. Experimental Setup

Simulation. We evaluate teams of $N \in \{10, 20, 30\}$ robots in an unbounded 2D workspace, with starts and goals sampled within an $11 \times 11\,\mathrm{m}^2$ region. Each team contains an equal number of DI, UNI, DD, CL, and FO robots. Start–goal pairs are separated by at least $4.0\,\mathrm{m}$, with an initial inter-robot separation of at least $1.5\,\mathrm{m}$. Each configuration is evaluated over 50 random trials with $\Delta t = 0.05\,\mathrm{s}$ and a maximum horizon of 1000 steps.

We use $x_r = 0.1\,\mathrm{m}$ for UNI/DD and $0.2\,\mathrm{m}$ for CL/FO. DI/UNI/DD use a $0.3\,\mathrm{m}$ radius, while CL/FO use a $0.3 \times 0.6\,\mathrm{m}$ footprint. We set $\lambda_1 = \lambda_2 = 2.0$. All methods use the same decentralized APF nominal controller [16], with goal-seeking weight $w = 0.9$ unless otherwise specified.

Metrics. We report *arrival rate* (AR), the fraction of robots reaching their goals within the rollout horizon; *violation count* (# Viol), the number of pairwise safety violations; and *mean violation depth* (Mean V), the average penetration $\max(0, R_{ij} - \|\mathbf{p}_i - \mathbf{p}_j\|)$ over violating robot pairs and timesteps. For the allocation ablation, we additionally measure local QP infeasibility.

B. Baselines

We compare CA-HCBF against three representative alternatives. **APF + Tracking** applies the nominal APF controller without a safety filter and varies $w \in \{0.1, 0.5, 0.9\}$, where w controls the trade-off between goal-seeking and collision avoidance, to characterize the safety–efficiency trade-off achievable through nominal avoidance alone. **APF + HOCBF** applies the same second-order CBF structure in the operational space but treats all robots as holonomic DI, thereby neglecting the model-dependent drift $\boldsymbol{\eta}_i$; this baseline isolates the importance of heterogeneity-aware safety modeling. Finally, **sRCBF (PD/APF)** applies the smooth robust CBF of [12] while treating neighboring robots as worst-case dynamic obstacles, using either its original PD nominal controller or the common APF controller[2].

C. Random Start–Goal Navigation

Table I summarizes the navigation results. CA-HCBF maintains high arrival rates of 97.4%, 94.7%, and 89.6% for $N = 10, 20, 30$, respectively, with consistently low safety violations; at $N = 30$, the mean violation depth is only $0.018\,\mathrm{m}$. In contrast, APF exhibits a clear safety–efficiency trade-off: at $N = 30$, $w = 0.9$ achieves 87.1% arrival but incurs 59.7 violations, whereas $w = 0.1$ reduces violations to 1.0 at the cost of only 15.5% arrival. APF + HOCBF, which neglects heterogeneous operational dynamics, degrades to 29.9% arrival with 25.2 violations at $N = 30$. Conversely, sRCBF yields relatively few violations but below-5% arrival for $N = 20$ and $N = 30$ due to its conservative worst-case treatment of neighboring robots. Overall, the results highlight the importance of heterogeneity-aware modeling and reciprocal responsibility sharing for maintaining both safety and navigation efficiency in dense interactions.

D. Effect of Capability-Aware Allocation

To isolate the effect of responsibility allocation, we compare *Equal* allocation ($\alpha_{ij} = \frac{1}{2}$), *Capability* allocation without feasibility-aware clipping, and the full *Capability+Clip* formulation, with all other controller components fixed. As shown in Fig. 2, local QP infeasibility increases with team size for all variants, while capability-aware allocation consistently reduces infeasibility by assigning more responsibility

[2]Additional implementation details are provided in the extended version.

TABLE I: Performance comparison across team sizes ($N \in \{10, 20, 30\}$, 50 trials each).

	$N = 10$			$N = 20$			$N = 30$		
Method	AR(%)↑	# Viol↓	MeanV↓	AR(%)↑	# Viol↓	MeanV↓	AR(%)↑	# Viol↓	MeanV↓
CA-HCBF (Ours)	**97.4**	0.1 (0.5)	0.001 (0.008)	**94.7**	1.2 (2.0)	**0.003 (0.008)**	**89.6**	5.1 (9.6)	**0.018 (0.035)**
APF + Tracking (w=0.9)	94.2	4.3 (2.8)	0.273 (0.112)	90.9	22.7 (6.4)	0.280 (0.075)	87.1	59.7 (11.6)	0.279 (0.066)
APF + Tracking(w=0.5)	89.4	2.1 (2.0)	0.200 (0.147)	86.1	13.5 (3.8)	0.267 (0.064)	80.7	37.9 (9.4)	0.271 (0.048)
APF + Tracking(w=0.1)	46.2	**0.0 (0.1)**	0.005 (0.034)	22.5	**0.1 (0.4)**	0.041 (0.124)	15.5	**1.0 (1.3)**	0.179 (0.206)
APF + HOCBF	42.4	2.5 (1.6)	0.196 (0.124)	36.6	11.5 (7.3)	0.271 (0.086)	29.9	25.2 (9.9)	0.264 (0.065)
APF + sRCBF	33.4	**0.0 (0.1)**	**0.000 (0.000)**	3.9	1.4 (3.1)	0.056 (0.097)	1.0	1.4 (2.8)	0.046 (0.078)
PD + sRCBF	24.6	1.1 (2.2)	0.028 (0.100)	4.4	5.7 (10.5)	0.029 (0.071)	0.9	3.2 (3.8)	0.040 (0.068)

Results are reported as mean (std). **Bold** with dark shading indicates best performance per metric; light shading indicates second best. AR(%): goal arrival rate; # Viol: number of pairwise safety violations; MeanV: mean violation depth (m).

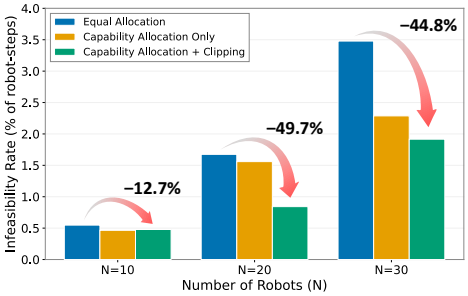


Fig. 2: Local infeasibility rates across different team sizes ($N \in \{10, 20, 30\}$). Lower values indicate improved decentralized feasibility.

to robots with greater directional control authority, with clipping providing further improvement in denser interactions. At $N = 30$, the full method reduces local infeasibility by 44.8% relative to equal allocation; for the more constrained FO and CL models, the infeasibility rate decreases from 13.47% to 6.62% and from 2.89% to 1.86%, respectively. These results show that capability-aware allocation improves decentralized feasibility by avoiding excessive safety responsibility assignments to robots with limited motion capability.

E. Physical Robot Validation

We validate CA-HCBF on five LIMO Pro [17] robots configured as DI, UNI, DD, CL, and FO. CA-HCBF coordinates all five robots through a shared central region while maintaining safe separation, whereas the worst-case sRCBF baseline becomes overly conservative and limits progress. This demonstrates how capability-aware safety coordination can support heterogeneous robots operating in tightly coupled shared physical spaces.

IV. Conclusion

We propose CA-HCBF, a decentralized framework that unifies five heterogeneous kinematic classes in a common second-order operational space and allocates pairwise safety responsibility according to each robot's directional motion capability. A feasibility-aware clipping mechanism further reduces unrealizable constraint assignments that can lead to local QP infeasibility. Simulations with up to 30 robots and a five-robot hardware experiment demonstrate improved safety and task efficiency over representative baselines. Future work will extend capability-aware responsibility allocation to neighborhood-level coordination for more jointly consistent decentralized safety decisions.

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