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CBF-Critic-Based Heading-Aware MPPI Navigation for Omnidirectional Mobile Robots

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Abstract

As the deployment of autonomous dual-arm wheeled humanoid robots and heavy-duty logistics robots accelerates, ensuring dynamic stability and collision-free navigation in narrow environments is critical. While 4-wheel independent steering (4WS) platforms offer superior maneuverability, their asymmetric rectangular footprints lead to severe collisions and rotational oscillations when managed by conventional circular-approximated controllers. To address these geometric limitations, this paper proposes a CBF-Critic-Based Heading-Aware MPPI navigation architecture. By modeling the robot's footprint as an Oriented Bounding Box (OBB), we integrate Control Barrier Functions (CBF) into the Model Predictive Path Integral (MPPI) framework. This elevates collision avoidance to a strict hard constraint, eliminating cost conflicts among multiple objectives. Furthermore, an online Adaptive Heading Critic dynamically enforces heading alignment in narrow passages using real-time LiDAR, suppressing unnecessary angular jerk. Extensive validations in simulation and on real-world 4WS hardware demonstrate a 100% collision-free success rate. Particularly in the region-locked parallel parking scenario, it was demonstrated that the proposed framework maximizes dynamic stability by reducing the maximum angular jerk by approximately 91.6% compared to the conventional soft-constraint baseline.

Keywords: Constrained Motion Planning, Collision Avoidance, Wheeled Robots, Control Barrier Function, Model Predictive Path Integral

1 Introduction

With the acceleration of automation, the deployment of autonomous dual-arm wheeled humanoid robots and heavy-duty logistics robots executing precise docking [1] has begun in earnest. To ensure safe and effective operation, these platforms require strict dynamic stability while in motion to prevent unnecessary oscillation or jerk of the mobile base. Omnidirectional bases, such as 4-wheel independent steering (4WS) platforms, provide superior maneuverability in narrow spaces. However, indiscriminately utilizing this mobility with their asymmetric rectangular footprints significantly increases the dynamic swept volume during rotation, raising collision risks [2]. Furthermore, continuous orientation changes not only induce centrifugal forces and jerk that degrade payload stability [3], but also incur severe steering scrub friction and hardware wear [4]. Therefore, a ‘Heading-Aware’ navigation strategy that aligns the body parallel to narrow surroundings is essential.

Model Predictive Path Integral (MPPI) control is a powerful sampling-based predictive controller [5, 6], but applying it to omnidirectional robots often generates inefficient trajectories by abusing all degrees of freedom [7]. Soft constraints via simple cost function tuning alone struggle to suppress this and guarantee collision avoidance because they fundamentally rely on ‘post-evaluation’—penalizing trajectories only after the robot enters a danger zone [8]. Most practical implementations of MPPI for mobile robot navigation typically rely on simplified circular kinematic models for distance evaluation to maintain computational efficiency [6, 7]. However, this oversimplification fails to reflect the rapidly changing dynamic swept volume of asymmetric robots, inevitably leading to conservative navigation or collisions. While an offline Multi-CBF Body-Aware strategy exists [9], it assumes global map knowledge without real-time hardware validation.

Recent literature has actively explored the integration of trajectory optimization with safety-critical frameworks within path integral control. For instance, Shield-MPPI [10] incorporates discrete-time CBF penalties into the critic cost while introducing a secondary repair step to alleviate safety violation issues. Similarly, BR-MPPI [11] enforces multiple inequality constraints using a learned Signed Distance Field (SDF) and true equality constraint projections, and EXACT-MPPI [12] achieves exact signed-distance navigation from raw point clouds for arbitrary footprints. While these approaches successfully enhance safety, they often introduce complex projection steps or heavy distance-field computations that can limit real-time agility in dense environments. In contrast, our proposed framework retains computational simplicity and real-time tractability by leveraging a discrete-time CBF critic augmented with an adaptive heading mechanism tailored for asymmetric footprints in tight channels.

To overcome these limitations, this paper proposes a ‘CBF-Critic-Based Heading-Aware MPPI’ framework for dual-arm wheeled humanoid robots and logistics platforms. The main contributions are threefold. First, an Online Adaptive Heading Critic dynamically estimates passage widths using real-time onboard 2D LiDAR [13, 14] and selectively activates a heading-lock mode in narrow passages, suppressing unnecessary jerk and maximizing computational efficiency. Second, an Asymmetric Footprint-Aware CBF trajectory evaluation is integrated into the MPPI framework to ensure absolute collision avoidance at the hard constraint level, safely controlling the

dynamic swept volume. Finally, unlike prior offline studies, the integrated algorithm was validated online on an actual 4WS Swerve Drive platform, demonstrating outstanding collision-free driving and dynamic stability in continuous narrow corridors and region-locked parallel parking scenarios.

2 Preliminaries

2.1 Control Barrier Function (CBF)

Consider a nonlinear control-affine system $\dot{\mathbf{x}} = f(\mathbf{x}) + g(\mathbf{x})\mathbf{u}$, where $\mathbf{x} \in \mathbb{R}^n$ is the state and $\mathbf{u} \in \mathcal{U} \subset \mathbb{R}^m$ is the input. A safe set $\mathcal{C}$ is defined by a continuously differentiable function $h : \mathbb{R}^n \rightarrow \mathbb{R}$ such that $\mathcal{C} = \{x \in \mathbb{R}^n \mid h(x) \geq 0\}$. The primary objective of safe control is to ensure forward invariance of $\mathcal{C}$ [15]. The function $h(\mathbf{x})$ is a Control Barrier Function (CBF) if there exists an extended class $\mathcal{K}$ function α such that for all $\mathbf{x} \in \mathcal{C}$:

$$\sup_{\mathbf{u} \in \mathcal{U}} [L_f h(\mathbf{x}) + L_g h(\mathbf{x})\mathbf{u}] \geq -\alpha(h(\mathbf{x})) \quad (1)$$

where $L_f h$ and $L_g h$ are Lie derivatives. In this paper, this continuous condition is discretized to evaluate trajectory safety within a sampling-based predictive controller.

2.2 Model Predictive Path Integral Control (MPPI)

MPPI solves nonlinear stochastic optimal control problems for discrete-time systems: $\mathbf{x}_{k+1} = F(\mathbf{x}_k, \mathbf{v}_k)$, with $\mathbf{v}_k \sim \mathcal{N}(\mathbf{u}_k, \Sigma)$ [16]. At each cycle, MPPI samples M random control sequences $V^{(m)}$ to yield predicted state rollouts $X^{(m)}$. A state cost $J(X^{(m)})$ is evaluated for each rollout, and the importance sampling weight is calculated as $w^{(m)} = \frac{1}{\eta} \exp\left(-\frac{1}{\beta}(J(X^{(m)}) - \rho)\right)$, where η normalizes the weights, β is the temperature parameter, and $\rho = \min_m J(X^{(m)})$. The optimal control sequence is then derived as the weighted average $\mathbf{u}_{0:K-1}^* = \sum_{m=1}^M w^{(m)} V^{(m)}$ and applied in a receding horizon fashion.

3 Problem Description

3.1 Robot Dynamics

This paper considers a swerve-drive mobile robot without steering limits (Fig. 1). The robot pose is defined in the world frame (x_w, y_w) , with body-frame velocities $(v_{b,x}, v_{b,y}, \omega_{b,z})$, wheelbase l , and track width t . For each wheel module $i \in \{1, 2, 3, 4\}$ located at $(l_{i,x}, l_{i,y})$, the velocity vector is expressed as:

$$\begin{aligned} (l_{1,x}, l_{1,y}) &= \left(\frac{l}{2}, \frac{t}{2}\right), & (l_{2,x}, l_{2,y}) &= \left(\frac{l}{2}, -\frac{t}{2}\right), \\ (l_{3,x}, l_{3,y}) &= \left(-\frac{l}{2}, \frac{t}{2}\right), & (l_{4,x}, l_{4,y}) &= \left(-\frac{l}{2}, -\frac{t}{2}\right). \end{aligned} \quad (2)$$

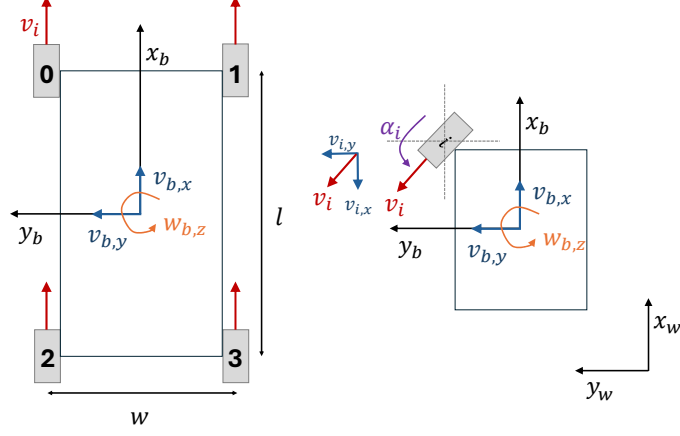


Fig. 1 Swerve drive robot kinematics

$$\begin{bmatrix} v_{i,x} \\ v_{i,y} \end{bmatrix} = \begin{bmatrix} v_{b,x} - \omega_{b,z} l_{i,y} \\ v_{b,y} + \omega_{b,z} l_{i,x} \end{bmatrix}. \quad (3)$$

The speed v_i and steering angle ϕ_i are then calculated as:

$$v_i = \sqrt{v_{i,x}^2 + v_{i,y}^2}, \quad \phi_i = \text{atan2}(v_{i,y}, v_{i,x}). \quad (4)$$

3.2 Obstacle Representation

Lethal obstacle cells from the local costmap are converted into a set of world-frame points:

$$\mathcal{O}_k = \{p_m^w = (p_{x,m}^w, p_{y,m}^w) \mid m = 1, \dots, M_k\}. \quad (5)$$

While existing studies often use circular approximations [17], such models fail to reflect the dynamic swept volume of asymmetric platforms [2]. To address this, we model the footprint as an Oriented Bounding Box (OBB). Obstacle points are transformed into the robot's local frame:

$$\begin{bmatrix} p_x^l \\ p_y^l \end{bmatrix} = \begin{bmatrix} \cos(-r_\theta) & -\sin(-r_\theta) \\ \sin(-r_\theta) & \cos(-r_\theta) \end{bmatrix} \begin{bmatrix} p_x^w - r_x \\ p_y^w - r_y \end{bmatrix}. \quad (6)$$

Given half-length a_x and half-width a_y , the shortest distance d_{rect} to the boundary is derived as [18]:

$$\begin{aligned} q_x &= |p_x^l| - a_x, & q_y &= |p_y^l| - a_y, \\ o_x &= \max(q_x, 0), & o_y &= \max(q_y, 0), \\ d_{rect} &= \sqrt{o_x^2 + o_y^2}. \end{aligned} \quad (7)$$

The minimum safe distance for state $\mathbf{x}_{i,k}$ is defined as $d_{i,k} = \min_{p_m \in \mathcal{O}_k} d(p_m, \mathbf{x}_{i,k})$.

3.3 Safety Constraint using CBF

The safe region is defined by $d_{i,k} - d_{th} \geq 0$, where d_{th} is the safety threshold. The corresponding Control Barrier Function (CBF) is:

$$h_{i,k} = w_h(d_{i,k} - d_{th}). \quad (8)$$

The safe set is denoted as $\mathcal{C} = \{\mathbf{x}_{i,k} \in \mathbb{R}^2 \times \mathbb{S} \mid h_{i,k} \geq 0\}$.

3.4 Navigation Objective

The MPPI-based navigation is formulated as a finite-horizon trajectory optimization problem. Instead of evaluating linearly separable stage costs at each individual time step, the central framework directly minimizes the total trajectory cost for each sampled control sequence rollout $\mathbf{V}_i$ over the prediction horizon N :

$$\begin{aligned} \min_{\mathbf{V}_i} \quad & \mathcal{J}_{\text{total}}(\mathbf{V}_i) \\ \text{s.t.} \quad & \mathbf{x}_{j+1} = f(\mathbf{x}_j, \mathbf{u}_j), \quad \mathbf{u}_j \in \mathcal{U}, \end{aligned} \quad (9)$$

where $i \in \{1, 2, \dots, M\}$ denotes the index of the M random control sequence rollouts sampled parallelly at each control cycle.

The total objective function is established by aggregating multiple non-linear trajectory critics to accommodate the power-law parameterization required for distinct constraints. Specifically, the framework encapsulates physical velocity limits $\mathcal{J}_{\text{const}}$, Control Barrier Function (CBF)-based safety guarantees $\mathcal{J}_{\text{CBF}}$, adaptive heading alignment $\mathcal{J}_{\text{heading}}$, and task-oriented path/goal convergence metrics $\mathcal{J}_{\text{path}}$, $\mathcal{J}_{\text{goal}}$, $\mathcal{J}_{\text{goal_angle}}$. The explicit mathematical formulations, individual component definitions, and the final linear combination of these non-linear parameterizations are detailed in Section 4 and summarized in Table 1.

4 CBF-Critic-Based Heading-Aware MPPI

4.1 CBF-Critic for MPPI

To evaluate predicted MPPI trajectories, the proposed CBF Critic assigns costs based on barrier function decay. Using the linear class- $\mathcal{K}$ function $\alpha(h) = \gamma h$, the continuous-time CBF condition [19] is $\dot{h} \geq -\gamma h$. Applying a forward Euler approximation with sampling time Δt yields:

$$\frac{h_{k+1} - h_k}{\Delta t} \geq -\gamma h_k \implies h_{k+1} \geq (1 - \gamma \Delta t) h_k. \quad (10)$$

Defining $\gamma_d = 1 - \gamma \Delta t$, the discrete-time CBF condition becomes $h_{k+1} \geq \gamma_d h_k$. The violation degree at step k is defined as the CBF cost $\mathcal{C}_k^{CBF} = \max(0, -h_{k+1} + \gamma_d h_k)$.

For the i -th trajectory rollout $\mathbf{V}_i$, the cumulative penalty $\mathcal{R}_i^{\text{CBF}}$ is:

$$\mathcal{R}_i^{\text{CBF}} = \begin{cases} C_{\text{col}}, & \min_{k \in \{1, \dots, N\}} d_{i,k} \leq d_{\text{th}}, \\ \sum_{k=1}^{N-1} \mathcal{C}_k^{\text{CBF}}, & \text{otherwise.} \end{cases} \quad (11)$$

A hard penalty C_{col} invalidates collisions, while a soft penalty accumulates margin violations. The final critic cost is $\mathcal{J}_{\text{CBF}}(\mathbf{V}_i) = \left(w_c \frac{\mathcal{R}_i^{\text{CBF}}}{N}\right)^p$. Although collision avoidance should theoretically be imposed as a hard constraint, our soft-constraint formulation, leveraging a massive collision cost (C_{col}) and a power-law exponent (p), effectively approximates hard-constraint behavior in practice while preserving real-time computational efficiency, thereby remaining compatible with the efficient rollout evaluation required by MPPI.

4.2 Adaptive Heading Critic

To dynamically alter the MPPI objective based on geometric constraints, a discrete state variable $S_t \in \{0, 1\}$ dictates the heading mode. The trajectory cost is $\mathcal{J}_{\text{heading}}(\mathbf{V}_k) = (1 - S_t)\mathcal{C}_{\text{path}}(\mathbf{V}_k) + S_t\mathcal{C}_{\text{lock}}(\mathbf{V}_k)$.

In Path-Angle Mode ($S_t = 0$), the robot aligns with the look-ahead target $\theta_{\text{ref},i} = \text{atan2}(y_{\text{goal}} - y_i, x_{\text{goal}} - x_i)$:

$$\mathcal{C}_{\text{path}} = \left(w_{\text{path}} \frac{1}{N} \sum_{i=1}^N |\ominus(\theta_i, \theta_{\text{ref},i})|\right)^p. \quad (12)$$

In Heading-Lock Mode ($S_t = 1$), the body aligns to a specific parallel angle θ_{lock} :

$$\mathcal{C}_{\text{lock}} = \left(w_{\text{lock}} \frac{1}{N} \sum_{i=1}^N |\ominus(\theta_i, \theta_{\text{lock}})|\right)^p, \quad (13)$$

where $\ominus$ returns the shortest angular distance. To prevent chattering, a hysteresis-based transition uses the estimated passage width $\hat{w}_t$:

$$S_t = \begin{cases} 1, & \text{if } \hat{w}_t \leq w_{\text{low}} \\ 0, & \text{if } \hat{w}_t \geq w_{\text{high}} \\ S_{t-1}, & \text{otherwise.} \end{cases} \quad (14)$$

Furthermore, while in Heading-Lock Mode ($S_t = 1$), if the environmental axis shifts—indicated by a sudden change in passage width ($\Delta \hat{w}_t < 0$)—the target heading θ_{lock} is dynamically updated to match the new environment, maximizing adaptability and preventing chattering.

Table 1 Critic cost used in the final MPPI objective function

Critic	Cost Function	Cost Definition
Constraint Critic	$\mathcal{J}_{\text{const}} = \left(w_{\text{const}} \sum_{j=1}^N \Delta t C_j \right)^p$	$C_j = \max(v_j - v_{\text{max}}, 0) + \max(v_{\text{min}} - v_j, 0)$ $v_j = \text{sign}(v_{x,j}) \sqrt{v_{x,j}^2 + v_{y,j}^2}$
CBF Critic	$\mathcal{J}_{\text{CBF}} = \left(w_{\text{CBF}} \frac{C^{\text{CBF}}}{N} \right)^p$	If $\min_j d_j \leq d_{\text{th}}$: $C^{\text{CBF}} = C_{\text{col}}$ Otherwise : $C^{\text{CBF}} = \sum_{j=1}^{N-1} \max(0, -h_{j+1} + \gamma_d h_j)$
Adaptive Heading Critic	$\mathcal{J}_{\text{heading}} = \left(\frac{1}{N} \sum_{j=1}^N C_j \right)^p$	If $S_t = 0$: $C_j = w_{\text{path}} \Theta(\theta_j, \theta_{\text{ref},j}) $ If $S_t = 1$: $C_j = w_{\text{lock}} \Theta(\theta_j, \theta_{\text{lock}}) $
Path Follow Critic	$\mathcal{J}_{\text{path}} = (w_{\text{path}} C)^p$	$C = \sqrt{(x_N - x_P)^2 + (y_N - y_P)^2}$
Goal Critic	$\mathcal{J}_{\text{goal}} = \left(w_{\text{goal}} \frac{1}{N} \sum_{j=1}^N C_j \right)^p$	$C_j = \sqrt{(x_j - x_g)^2 + (y_j - y_g)^2}$
Goal Angle Critic	$\mathcal{J}_{\text{goal_angle}} = \left(w_{\text{goal_angle}} \frac{1}{N} \sum_{j=1}^N C_j \right)^p$	$C_j = \theta_j - \theta_g $

4.3 Final MPPI Cost Function

The final objective combines the proposed critics with standard navigation terms:

$$\mathcal{J}_{\text{total}} = \mathcal{J}_{\text{const}} + \mathcal{J}_{\text{CBF}} + \mathcal{J}_{\text{heading}} + \mathcal{J}_{\text{path}} + \mathcal{J}_{\text{goal}} + \mathcal{J}_{\text{goal_angle}} \quad (15)$$

Detailed definitions for each critic—evaluating physical constraints, safety, heading alignment, and goal convergence—are summarized in Table 1.

5 Experiment

5.1 Experimental Setup

To validate the proposed algorithm, simulations and real-world experiments were conducted using a 4WS platform (0.9×0.4 m footprint). The ROS 2 Nav2 MPPI controller

Table 2 MPPI controller parameters applied in the simulation environment

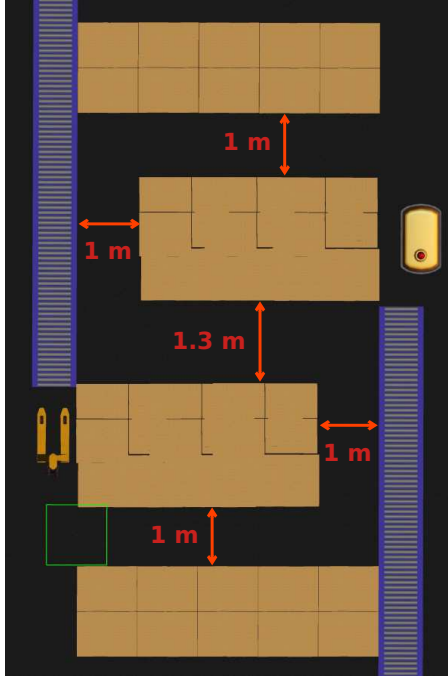
Category	Parameter	Symbol	Value	Unit
MPPI Core	Number of samples (Batch size)	K	300	-
	Prediction horizon	N	40	steps
	Time step interval	Δt	0.05	s
Sampling Noise	Linear velocity noise std.	σ_x, σ_y	0.2	m/s
	Angular velocity noise std.	σ_θ	0.1	rad/s
Kinematic Limits	Max linear velocity	$v_{x,\max}, v_{y,\max}$	0.5	m/s
	Max angular velocity	$\omega_{\max}$	0.3	rad/s
Critic Weights	Goal distance cost weight	w_{goal}	5	-
	Goal angle cost weight	$w_{\text{goal_angle}}$	3	-
	Path follow cost weight	w_{path}	5	-
	Constraint (Kinematics) cost	w_{const}	4	-
	CBF safety cost weight	w_{CBF}	5	-
	Adaptive heading (Path angle)	$w_{\text{path_angle}}$	2	-
	Adaptive heading (Lock)	w_{lock}	5	-
	Fixed region lock weight	$w_{\text{region_lock}}$	10	-
CBF Settings	CBF decay rate parameter	α	0.7	-

ran at 20 Hz on the robot’s onboard computer (ASUS NUC 15 Pro, Intel Core Ultra 5 225H, 16GB RAM), ensuring real-time feasibility despite the computational overhead of OBB trajectory evaluations. For full reproducibility, the core MPPI parameter configurations applied in the simulation—such as the batch size ($K = 300$) and prediction horizon ($N = 40$)—are summarized in Table 2. Additionally, the complete source code is open-sourced and available in our GitHub repository ¹. To ensure fairness, fundamental critic weights were fixed across all models. Success was strictly defined as flawless navigation without a single physical collision.

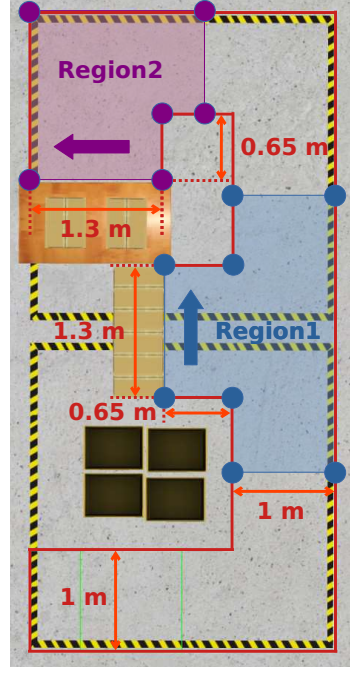
5.2 Case Study 1: Narrow Corridor Navigation

A Gazebo world featuring a narrow corridor with consecutive right-angle turns was constructed (Fig. 2a). As summarized in Table 3, conventional circular approximation inherently failed due to the paradox of conservative inflation. Forcibly increasing the inscribed radius to protect the asymmetric swept volume expanded the absolute no-entry zone, completely blocking the narrow passage (Fail 5, Fig. 3). Conversely,

¹<https://anonymous.4open.science/r/Heading-Aware-CBF-MPPI-Anonymous/README.md>



(a) Case Study 1



(b) Case Study 2

Fig. 2 Gazebo simulation environments.

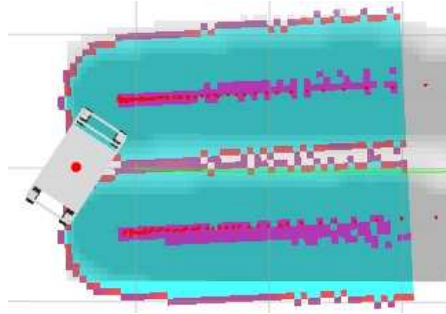


Fig. 3 Entry failure scenario due to conservative inflation settings (**Fail 5**): As a result of forcibly increasing the robot radius, the absolute no-entry zone completely blocks the narrow passage, causing the robot to abort entry and become stuck.

reducing the radius to force passage failed to protect the rectangular corners, resulting in fatal rollovers (Fail 1-4). Furthermore, rectangular soft-constraint models (M2, M5) suffered from cost compromises, leading to unavoidable wall collisions.

The quantitative results (Table 4) clearly demonstrate the superiority of the proposed method. M6 (CBF + OBB + Adaptive Heading) achieved a 100% collision-free success rate. Unlike conventional post-evaluating obstacle critics, by elevating safety

Table 3 Configuration of evaluation models for progressive component analysis and qualitative results in the narrow consecutive corridor (Case Study 1).

Model	Inflation Radius	Critic Type	Footprint	Heading Control	Status	Remarks
Fail 1–4	0.25 m	Obstacle	Circular/Rectangular	Free / Adaptive	Fail	Rollover at corners due to the limitations of post-evaluation.
Fail 5	0.45 m	Obstacle	Circular (0.4 m)	Free	Fail	Passage blocked by the absolute no-entry zone.
M1 (Base)	0.45 m	Obstacle	Circular (0.4 m)	Free	Completed	Multiple collisions.
M2	0.45 m	Obstacle	Rectangular	Free	Completed	Severe rotational oscillation.
M3	–	CBF	Rectangular	Free	Completed	Collision-free, but severe rotational oscillation.
M4	0.45 m	Obstacle	Circular (0.4 m)	Adaptive	Completed	Multiple collisions.
M5	0.45 m	Obstacle	Rectangular	Adaptive	Completed	Minor collisions.
M6 (Ours)	–	CBF	Rectangular	Adaptive	Completed	Collision-free, with maximized rotational stability.

Table 4 Quantitative evaluation results of the navigation models in the narrow consecutive corridor scenario (Case Study 1).

Model	Safety		Stability			
	Avg. Collision	Success Rate	Total Heading Var. (rad)	Max / Avg Angular Accel. (rad/s ²)	Max / Avg Angular Jerk (rad/s ³)	Max / Avg Linear Jerk (m/s ³)
M1 (Base)	13.40	0%	7.91	2.50 / 0.25	50.95 / 2.53	22.62 / 1.10
M2 (OBB)	0.07	93%	6.37	0.89 / 0.11	18.07 / 0.91	37.74 / 0.66
M3 (CBF, OBB)	0.00	100%	6.85	0.80 / 0.11	27.35 / 1.01	37.44 / 0.68
M4 (Adpt)	6.27	0%	4.93	1.83 / 0.22	43.23 / 2.49	36.94 / 1.16
M5 (OBB, Adpt)	1.93	0%	3.66	1.36 / 0.10	24.71 / 1.05	33.25 / 0.59
M6 (Ours)	0.00	100%	3.84	1.15 / 0.10	25.11 / 1.01	34.53 / 0.59

to a hard constraint, M6 pre-invalidated dangerous trajectories prior to entering collision zones, ensuring a perfectly smooth angular velocity profile without control spikes (Fig. 4) and executing a stable crab-walk (Fig. 5). Real-world validation mirrored these stable, collision-free dynamics (Fig. 6).

5.3 Case Study 2: Task-Oriented Region-Locked Control

To verify task-oriented docking, a logistics map with predefined loading and parking regions was designed (Fig. 2b). To enforce this, a custom 'Heading Fixed Region Critic' was implemented, defining control zones via map coordinate vertices and dynamically assigning absolute target headings and penalty weights upon region entry.

As shown in Table 5, the circular baseline (Fail 1) rolled over due to geometric constraints. The rectangular soft-constraint baseline (M5) completed the task but averaged 2.13 collisions. As detailed in Table 6, the soft constraint controller falls into

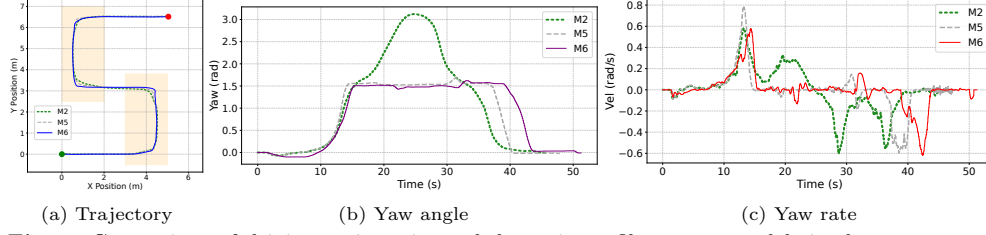


Fig. 4 Comparison of driving trajectories and dynamic profiles across models in the narrow consecutive right-angle corridor (Case Study 1). **(a) Trajectory:** M2 (OBB, Free) exhibited noticeable body twisting, M5 (OBB, Adaptive) partially reduced this effect, and M6 (Ours) showed the most stable trajectory. **(b) Yaw angle:** M2 showed large yaw fluctuations, M5 partially suppressed them, and M6 maintained a stable response. **(c) Yaw rate:** M2 and M5 exhibited larger fluctuations and spike-like responses, whereas M6 produced the smoothest profile.

Table 5 Configuration of evaluation models for task-oriented region-locked control and qualitative results in the logistics warehouse scenario (Case Study 2).

Model	Inflation Radius	Critic Type	Footprint	Heading Control	Status	Remarks
M4	0.45 m	Obstacle	Circular (0.2 m)	Fixed Region	Fail	Rollover.
M5	0.45 m	Obstacle	Rectangular (OBB)	Fixed Region	Completed	Collisions and goal convergence instability.
M6 (Ours)	–	CBF	Rectangular (OBB)	Fixed Region	Completed	Collision-free, with maximized rotational stability.

Table 6 Quantitative evaluation results of safety and dynamic stability in the logistics warehouse parking scenario (Case Study 2).

Model	Safety		Stability			
	Avg. Collision	Success Rate	Total Heading Var. (rad)	Max / Avg Angular Accel. (rad/s ²)	Max / Avg Angular Jerk (rad/s ³)	Max / Avg Linear Jerk (m/s ³)
M5 (OBB)	2.13	0%	4.74	2.60 / 0.07	184.97 / 0.79	34.94 / 0.32
M6 (CBF)	0.00	100%	3.54	0.55 / 0.05	15.51 / 0.38	30.47 / 0.35

a mathematical dilemma, struggling to simultaneously minimize three severely conflicting objectives in a single cost equation: obstacle avoidance, heading lock, and goal convergence. This convergence instability triggered control collapse in M5, exploding max angular jerk to 184.97 rad/s³ (Fig. 7).

By completely decoupling collision avoidance as a hard constraint, M6 achieved 0.00 collisions and suppressed max angular jerk to 15.51 rad/s³ (a 91.6% reduction). Real-world experiments identically demonstrated seamless, collision-free region-constrained parallel parking (Fig. 9).

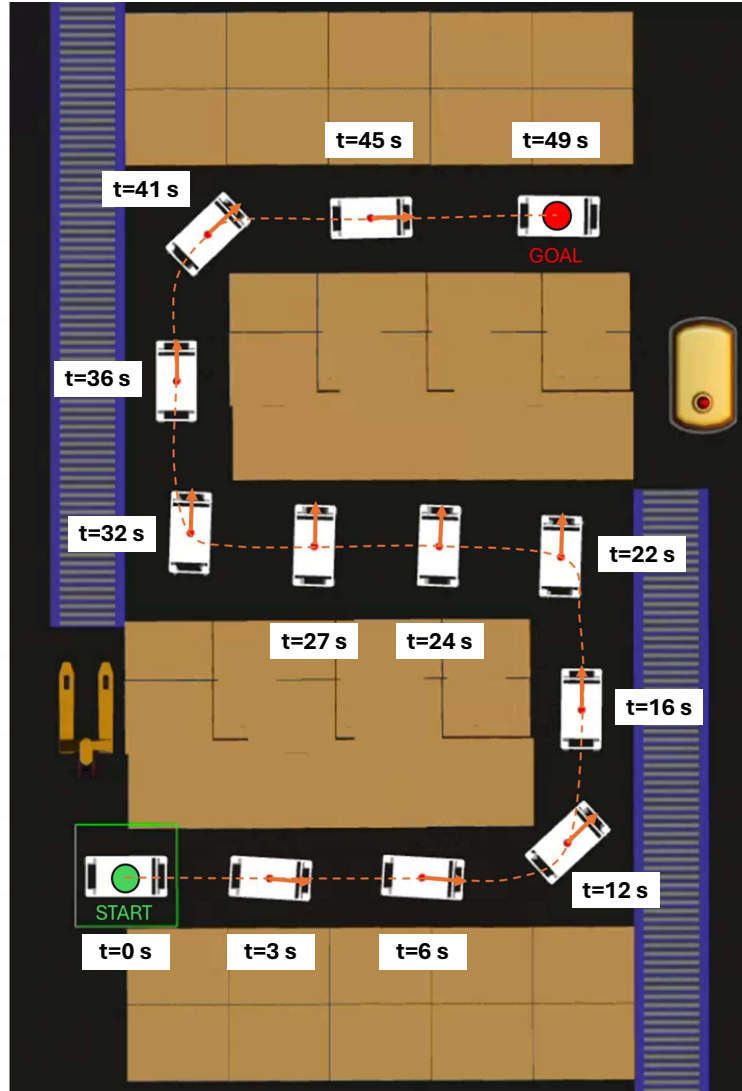


Fig. 5 Overlaid time-step snapshots showing the trajectory and heading direction in Case Study 1 (Simulation).

6 Discussion

6.1 The Paradigm Shift from Soft to Hard Constraints

Summing multiple objective functions into a single soft constraint inevitably provokes convergence instability. In narrow spaces, the controller falls into a mathematical dilemma where it erroneously concludes that minor wall collisions are more optimal than enduring massive heading penalties. By completely decoupling collision avoidance from this cost summation and elevating it to an absolute hard constraint (CBF,

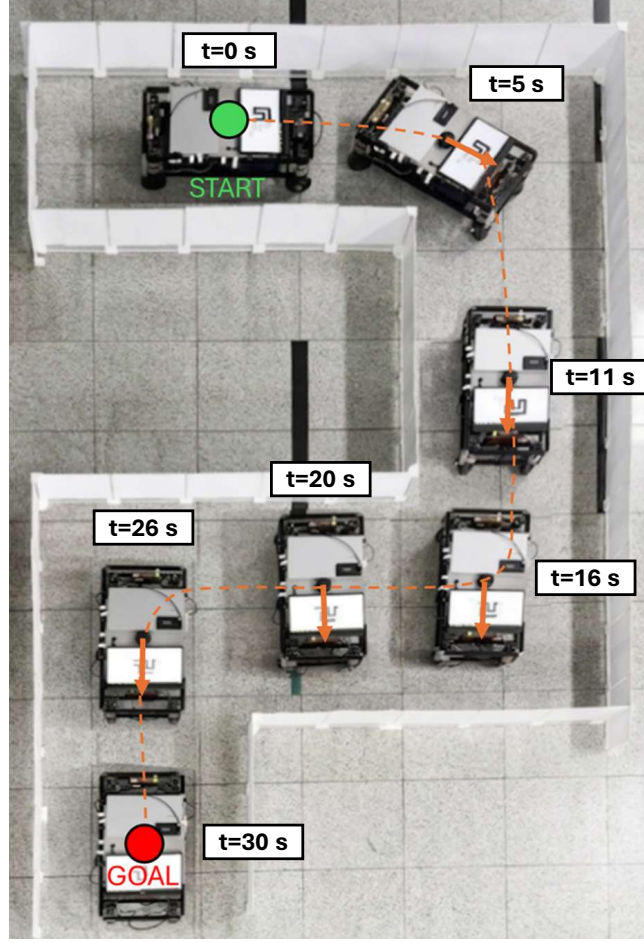


Fig. 6 Overlaid time-step snapshots showing the trajectory and heading direction in the real-world validation of Case Study 1.

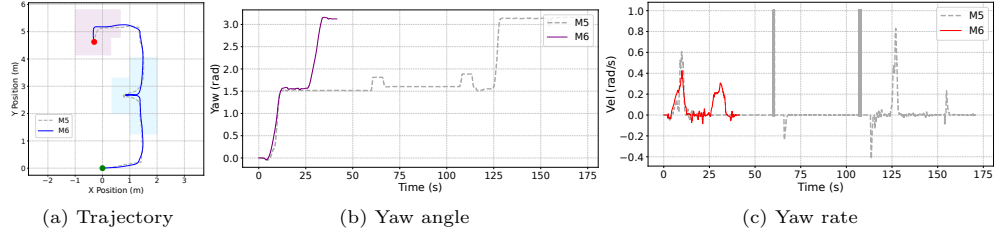


Fig. 7 Comparison of dynamic behavior and angular velocity profiles in the logistics warehouse loading and parking environment (Case Study 2). **(a) Trajectory:** M5 completed the maneuver with a substantially longer execution time and hesitant motion, whereas M6 completed the maneuver in a shorter time with a stable trajectory. **(b) Yaw angle:** M5 showed irregular yaw-angle variations, while M6 maintained a smoother response. **(c) Yaw rate:** M5 exhibited large spike-like yaw-rate responses indicating control degradation caused by cost conflict. In contrast, M6 produced a smooth profile through the separation of concerns enabled by the CBF.

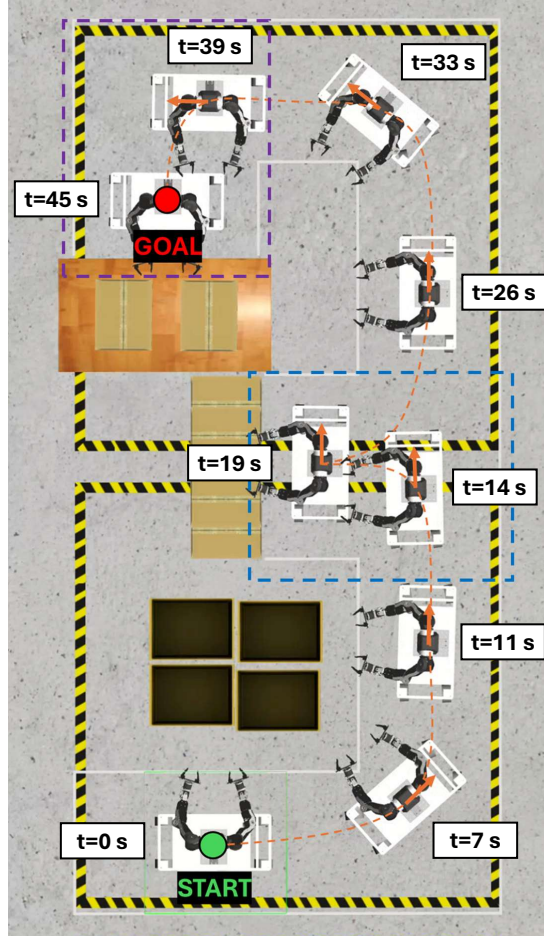


Fig. 8 Overlaid time-step snapshots showing the trajectory and heading direction in Case Study 2 (Simulation). Blue and purple dashed regions indicate heading-fixed zones.

subject to $h(x) \geq 0$), the proposed architecture achieves a strict separation of concerns. Freed from cost compromises, the optimizer dedicates its full computational power solely to goal convergence and heading alignment, guaranteeing highly stable, collision-free navigation without control collapse.

6.2 Generality to Arbitrary Path Geometries

While Case Study 1 verified performance in orthogonal corners, the proposed architecture extends seamlessly to arbitrary geometries. Because the Adaptive Heading Critic derives its reference heading dynamically, it operates flawlessly in non-orthogonal intersections without parameter tuning. As shown in Fig. 10, the robot proactively aligns to changing curvatures, maintaining dynamic safety margins and proving its readiness for irregular, real-world industrial environments.

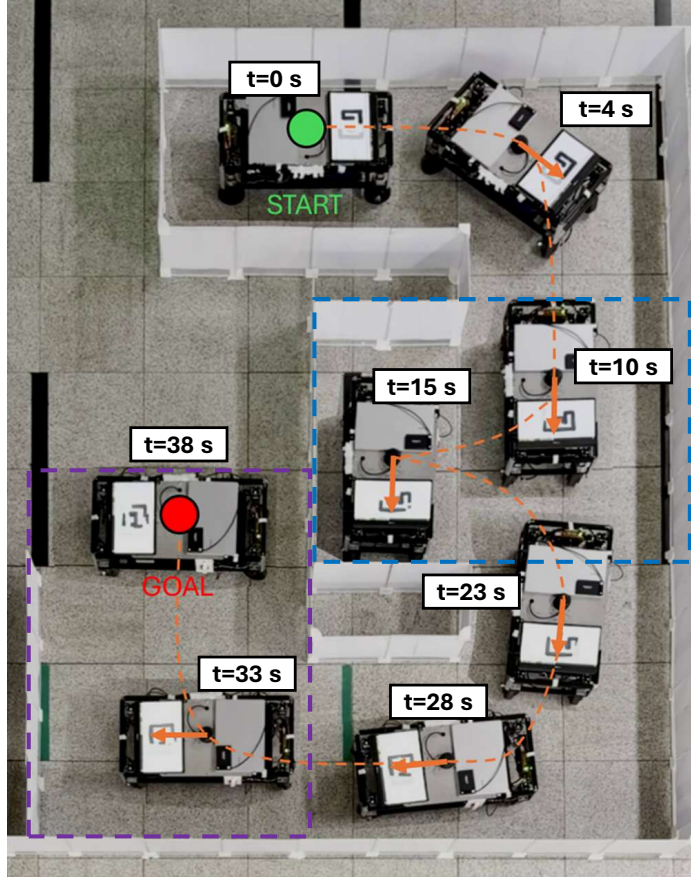


Fig. 9 Robot trajectory, heading, and time steps in the real-world validation of Case Study 2.

6.3 Computational Overhead and Practicality

Although computing OBB distances for every trajectory sample incurs higher CPU overhead than a circular critic, the proposed architecture completes optimization within 30 ms. This stably secures a 20 Hz control frequency onboard, proving its real-time computational efficiency and practicality for immediate deployment in industrial fields. Furthermore, empirical sensitivity analysis on the collision penalty C_{col} confirmed that the proposed framework is not over-fitted to specific maps. As long as C_{col} is maintained sufficiently larger than the navigation goal costs, the hard-constraint approximation remains robust across various dense environments without requiring map-specific parameter tuning.

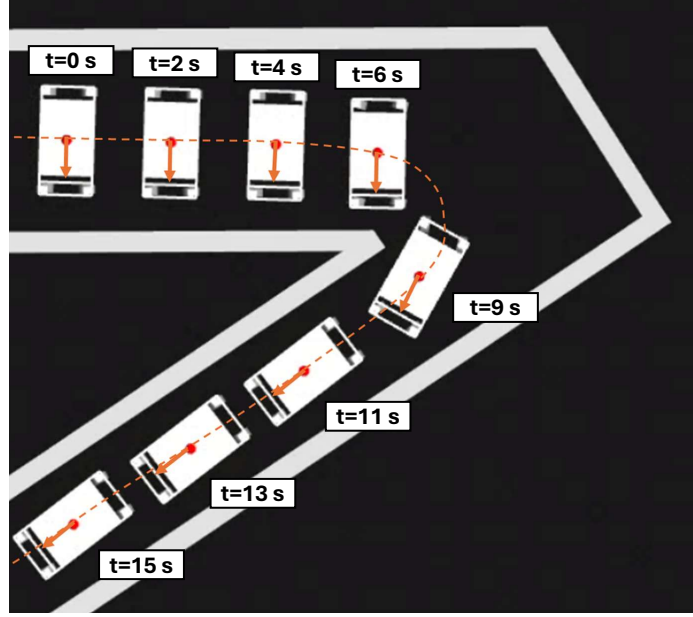


Fig. 10 Driving results in a non-orthogonal intersection. The Adaptive Heading Critic dynamically adjusts the robot’s heading to fit the arbitrary path geometry without any parameter tuning.

7 Conclusion

This paper proposed a CBF-Critic-Based Heading-Aware MPPI architecture to overcome the geometric control limits—specifically, collisions and rotational oscillations—of asymmetric 4WS platforms. By elucidating the fundamental limitations of conventional inscribed-radius-based post-evaluation controllers, we introduced a prior trajectory invalidation mechanism via hard constraints. Consequently, the proposed algorithm achieved a 100% collision-free success rate and maximized dynamic stability in both narrow consecutive corridors and region-locked environments. This overwhelming ride comfort and stability serve as a foundational technology not only for the safe transport of heavy-duty logistics robots but also for controlling the mobile bases of dual-arm wheeled humanoid robots, where precise upper-body manipulation is essential. Future work will extend the proposed framework to address dynamic obstacle avoidance and multi-robot cooperative navigation in highly cluttered environments.

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