Safe Navigation for Mecanum Wheeled Robots via Enhanced MPC with Discrete-Time Control Barrier Functions

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***Abstract*—Ensuring safe navigation for mobile robots in dynamic environments remains a major challenge, particularly when dealing with unpredictable moving obstacles. This paper proposes an enhanced control framework that integrates Model Predictive Control (MPC) with Discrete-Time Control Barrier Functions (D-CBF) to achieve both optimal path planning and real-time collision avoidance. The approach is validated through Python-based simulations and real-world experiments using a ROS-integrated Mecanum-wheeled robot. A Marvelmind ultrasonic indoor positioning system provides accurate real-time localization for both the robot and dynamic obstacles. Results from various navigation scenarios demonstrate that the proposed MPC–D-CBF controller effectively maintains safety margins and achieves reliable trajectory tracking, confirming its potential for deployment in dynamic real-world environments.**

***Keywords*—Mobile Robots, Marvelmind, Dynamic Obstacles, Model Predictive Control (MPC), Discrete-Time Control Barrier Functions (D-CBF).**

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I. Introduction

MOBILE robots have experienced rapid advancements over the last few decades, finding widespread applications in the manufacturing, healthcare, agriculture, and exploration industries. A fundamental requirement for their performance is the presence of reliable navigation systems capable of adapting to various operational environments. As robots increasingly operate within dynamic and complex settings, ensuring safe and efficient navigation becomes critical, particularly in contexts that include dynamic obstacles, such as humans, vehicles, or other moving objects [1], [2]. Safe navigation involves not only successful achievement to the desired destination but also the prevention of potential collisions, thereby presenting a significant challenge within the field of robotics [3], [4].

Dynamic environments complicate mobile robot navigation, requiring systems to adapt in real-time. Predicting the motion of dynamic obstacles remains complex due to the inherent uncertainties in their trajectories and behaviors. This complexity requires sophisticated motion prediction and decision-making algorithms to ensure safe navigation in real-world scenarios [5], [6]. Several approaches, such as deep reinforcement learning, have been explored to enhance robot navigation in unpredictable environments, allowing them to adapt dynamically to changes in their surroundings [7], [8]. Recent developments have integrated real-time predictive modeling to address trajectory uncertainties, allowing adaptive navigation among humans, vehicles, and other moving objects [9], [10]. Additionally, methods of semantic navigation utilizing deep reinforcement learning have been investigated to enhance decision-making in highly dynamic environments [11]. Advanced control methods like Model Predictive Control (MPC) provide solutions by generating optimal paths and ensuring collision avoidance [12]. When combined with Discrete-Time Control Barrier Functions (D-CBF), MPC enhances safety by enforcing collision-prevention constraints in dynamic settings [13], [14]. This combination leverages MPC's optimization capabilities with D-CBF's safety guarantees to handle complex scenarios involving dynamic obstacles [15].

Recent technological advancements, including the adoption of LiDAR, cameras, and radar sensors, have enhanced robots' capabilities to detect and track dynamic

obstacles in real time [16]. Studies have shown that integrating sensor fusion techniques can improve the accuracy of obstacle detection and reduce the risk of collisions [17], [18]. The use of precise localization systems, such as Marvelmind GPS, has further advanced the capabilities of mobile robots in indoor environments. Marvelmind GPS provides accurate positioning data using ultrasonic signals, enabling robots to navigate and avoid obstacles with high precision.

This study focuses on combining advanced control algorithms with sensor technologies to improve the safety of mobile robot navigation systems. The framework is validated through Python simulations and hardware experiments to ensure reliable navigation in real-world scenarios.

More specifically, the contributions of this study are as follows:

1. Integrated MPC with D-CBF Control Framework: Real-time controller combining MPC for trajectory optimization with D-CBF to enforce safety constraints.
2. Marvelmind Indoor Positioning System Implementation: Leveraging Marvelmind ultrasonic-based indoor-positioning data for real time localization of both the robot and dynamic obstacles within the MPC with D-CBF control framework.
3. Comprehensive Performance Evaluation: Quantitative evaluation leveraging Python-based simulations and ROS-integrated hardware experiments to validate the reliability and safety of the proposed navigation system under varying scenarios.

The rest of the paper is structured as follows: Section II describes the proposed method, Section III outlines the experimental setup, Section IV discusses the results, and Section V concludes with a summary of the findings.

II. Literature Review

Mobile robot navigation in dynamic environments has emerged as a key research area, driven by the growing need for safe and adaptive robotic systems in complex operational settings. Various studies have focused on ensuring collision avoidance and trajectory optimization in environments populated by humans, vehicles, and other moving obstacles [1], [2], [3], [4]. As highlighted in previous research, one of the primary challenges lies in the ability to detect and respond to the unpredictable behavior of dynamic elements in real time [5], [6].

Recent approaches emphasize the importance of predictive and adaptive decision-making to manage navigation under uncertainty. Deep reinforcement learning has been explored as a viable method to facilitate robot learning in dynamic contexts, enabling autonomous systems to adapt to unexpected environmental changes [7], [8]. Alongside this, predictive trajectory modeling has been increasingly integrated into control frameworks, allowing robots to anticipate motion patterns and maintain safe navigation paths among multiple moving agents [9], [10]. Furthermore, the incorporation of semantic understanding into navigation—particularly through learning-based approaches—has proven effective in improving situational awareness and real-time decision-making [11].

Model Predictive Control (MPC) stands out as a robust strategy for motion planning, offering dynamic optimization of control inputs while accounting for system constraints. Its real-time capability to recalculate optimal trajectories makes MPC well-suited for environments where conditions change rapidly [12]. When combined with Discrete-Time Control Barrier Functions (D-CBF), MPC frameworks are able to enforce strict safety boundaries, ensuring that robots avoid collisions even in the presence of moving obstacles [13], [14], [15]. This synergy has been shown to yield both optimal and safe behavior, addressing the dual objectives of goal achievement and risk mitigation.

Technological advancements in sensing and localization have further empowered these control strategies. The integration of real-time sensory data—sourced from LiDAR, cameras, or radar—has significantly improved robots' ability to track obstacles and navigate safely [16], [17], [18]. Particularly in indoor settings, ultrasonic-based systems like Marvelmind GPS have emerged as reliable tools for high-precision localization. By delivering accurate position data, Marvelmind systems enhance the robot's awareness of its surroundings, thereby supporting safe navigation and obstacle avoidance in structured environments.

To ensure the reliability of proposed methods, simulation environments and hardware platforms are critical. Python-based simulations and Robot Operating System (ROS) provide flexible environments for algorithm development and performance evaluation. Using tools like RViz and Gazebo, researchers can test integrated control systems under diverse and replicable conditions, ensuring the practical applicability of algorithms before deployment. Such platforms have proven especially valuable when validating the interaction between MPC, D-CBF, and real-time localization inputs, like those from Marvelmind systems.

Overall, the literature suggests that integrating predictive control strategies with sensor-driven localization systems significantly advances the state-of-the-art in mobile robot navigation. This convergence of robust control theory, machine learning, and real-time sensing paves the way for safer and more intelligent autonomous systems capable of operating effectively in dynamic and uncertain environments [1]– [18]. In addition, Mendes et al. [33] presented an open-access implementation of visual obstacle avoidance using odometric data in indoor mobile robot navigation. Their approach demonstrated the effectiveness of lightweight sensor fusion for real-time decision-making, which aligns with the objectives of our proposed MPC–D-CBF framework.

III. Problem Formulation

A. Mecanum-Wheeled Mobile Robot Kinematic Model

This study focuses on implementation of a Model Predictive Control (MPC) method enhanced with discrete-time Control Barrier Function (D-CBF) on a holonomic Mecanum-wheeled robot. The platform’s four independently actuated Mecanum wheels enables omnidirectional motion, allowing the proposed controller to be evaluated across the full range of planar maneuvers.

The holonomic kinematics model is commonly utilized to characterize the robot's movement through its linear and angular velocities. Fig. 1 illustrates the Mecanum-wheeled

robot model employed in this research.

The state vector of the robot is given by:

$$\boldsymbol{x}_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} \tag{1}$$

The first two (spatial) components of the state (x, y) represent the position of the robot in the planar coordinate frame, while the angle θ corresponds to the heading of the robot.

The robot is controlled with input:

$$\boldsymbol{u}_k = \begin{bmatrix} v_{long|k} \\ v_{lat|k} \\ \omega_k \end{bmatrix} \tag{2}$$

*w*here $v_{long|k}$ r represents the linear velocity along the x-axis, corresponding to the robot's forward and backward motion; $v_{lat|k}$ denotes the linear velocity along the y-axis, which relates to the lateral (side-to-side) movement; ω_k is an angular velocity around the z-axis, defining rotational movement of the robot about its vertical axis.

The kinematic equation expresses the robot's motion in a discrete form can be derived as:

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} + T_s \begin{bmatrix} v_{long|k}\cos(\theta_k) - v_{lat|k}\sin(\theta_k) \\ v_{long|k}\sin(\theta_k) + v_{lat|k}\cos(\theta_k) \\ \omega_k \end{bmatrix} \tag{3}$$

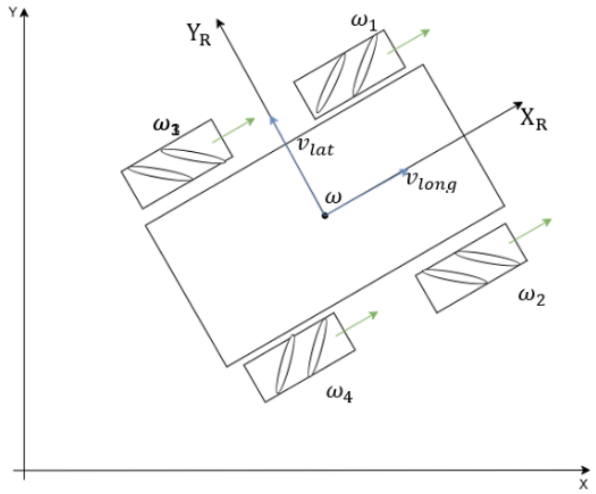


Fig. 1. Mecanum-wheeled Mobile Robot Kinematics

where T_s is the time step, duration between consecutive updates, which is used to calculate the motion incrementally.

B. Model Predictive Control (MPC) Formulation

Model Predictive Control (MPC) is an advanced control approach that optimizes control inputs by predicting the future behavior of a system over a finite horizon. First introduced in the early 1970s—with Karl Jensen's work on predictive control using a finite prediction horizon in 1971 [27]—MPC has since become a widely used of advanced control strategies for dynamic systems.

In autonomous navigation, MPC's ability to handle system dynamics and constraints makes it particularly well suited for real-time trajectory planning and obstacle avoidance. By solving a constrained optimization problem at each timestep, MPC generates control actions that steer the robot along an optimal path while respecting the hardware limits and safety requirements [19],[28].

A common enhancement for safety-critical applications is the integration of Discrete-time Control Barrier Function (D-CBF). D-CBFs impose state-based constraints that guarantee forward invariance of a safe set, effectively preventing collisions by modifying the MPC control law when necessary [21],[24],[25]. This combined MPC/D-CBF framework has been shown to maintain real-time performance in dynamic environments, offering both computational efficiency and safety guarantees [26].

Recent developments have further improved MPC's responsiveness through multi-rate control schemes. In a unified multi-rate approach, high-level MPC planning operates at a slower rate, while lower-level control updates—such as CBF-based safety checks—run more frequently. This coordination enhances the robot's ability to simultaneously address trajectory tracking and rapid obstacle avoidance, even under uncertain and fast-changing conditions [22],[23].

Recent studies have expanded the application of MPC by incorporating advanced techniques such as collision avoidance and optimization-based control to handle constraints in real-time. Optimization methods ensure efficient control while maintaining safety, as demonstrated in collision avoidance systems [29]. Additionally, MPC combined with control-Lyapunov functions has been shown to be effective for the stabilization and control of robotic systems in complex environments [30].

In this study, we utilize a linearized kinematic model of the mobile robot to formulate the MPC problem. At each control step, the linear MPC predicts the robot's future state and computes an optimal sequence of control inputs by minimizing a quadratic cost function subject to linear dynamics and D-CBF safety constraints. The resulting control law thus ensures both path efficiency and collision avoidance in real time [20].

To achieve accurate prediction in Model Predictive Control (MPC), the kinematic model is first linearized and formulated in discrete - time. However, real-world implementation requires enforcing dynamic feasibility and system constraints to ensure safety and control authority.

The robot's discrete-time kinematic dynamics are given by:

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + T_s \cdot \mathbf{B}(\theta_k) \cdot \boldsymbol{u}_k \tag{3}$$

Where:

- $\boldsymbol{x}_k \in \mathbb{R}^n$ is the state vector at step k.
- $\boldsymbol{u}_k \in \mathbb{R}^m$ is the control input.
- $\mathbf{B}(\theta_k)$ is the rotation matrix depending on the robot orientation.
- T_s is the sampling time.

The robot's linearized kinematics are described by a discrete-time state-space model:

$$\boldsymbol{x}_{k+1} = \mathbf{A}\boldsymbol{x}_k + \mathbf{B}\boldsymbol{u}_k \tag{4}$$

Where:

- $\boldsymbol{x}_k \in \mathbb{R}^n$ is the state vector at step k.
- $\boldsymbol{u}_k \in \mathbb{R}^m$ is the control input.
- **A** and **B** are the system matrices obtained from linearizing the robot kinematics around the current operating point.

To effectively implement the Model Predictive Control (MPC) scheme, the robot's dynamic model is discretized and linearized around the current operating point. This results in the standard discrete-time linear state-space representation, $\boldsymbol{x}_{k+1} = \mathbf{A}\boldsymbol{x}_k + \mathbf{B}\boldsymbol{u}_k$, where $\mathbf{A} \in \mathbb{R}^{n\times n}$and $\mathbf{B} \in \mathbb{R}^{n\times m}$ are the state transition and input matrices, respectively. These matrices are typically obtained through Jacobian linearization of the original nonlinear kinematic model, evaluated at the current state and input.

To ensure the feasibility of the predicted trajectories and maintain the robot's operation within realistic and safe bounds, several constraints are imposed on both the state and control input. State constraints are defined as $\boldsymbol{x}_{min} \le \boldsymbol{x}_k \le \boldsymbol{x}_{max}$ for all prediction steps $k \in [0, N]$, which restrict the robot's positions and orientations to remain within the boundaries of the operating environment. Meanwhile, the input constraints are formulated as $\boldsymbol{u}_{min} \le \boldsymbol{u}_k \le \boldsymbol{u}_{max}$ for all $k \in [0, N-1]$, reflecting the physical limitations of the robot's actuators. Specifically, these input bounds limit the forward and lateral velocities as well as the angular velocity, ensuring that the absolute values of the longitudinal velocity v_{long}, lateral velocity v_{lat}, and angular velocity ω do not exceed their respective maximum values v_{max} and ω_{max} . These constraints are critical to prevent unsafe or infeasible control actions during real-time execution.

MPC will be used to control the mobile robot based on the predicted movement of the model and optimize it based on the objective function to plan a safe and efficient path. At each timestep, MPC solves the following finite-horizon optimal control problem:

$$min \sum_{k=0}^{N-1} (\frac{1}{2}(\boldsymbol{x}_{des|k} - \boldsymbol{x}_k)^T Q(\boldsymbol{x}_{des|k} - \boldsymbol{x}_k) + \frac{1}{2}\boldsymbol{u}_k^T R \boldsymbol{u}_k \qquad (5)$$

Where $\mathrm{x}_{des}(k)$ the desired state at time step k; $\mathrm{x}(k)$ is the actual state of the system at time step k; Q is the weight matrix penalizing state errors; R is the weight matrix penalizing control inputs, and $\mathrm{u}(k)$ is the control input at time step k.

System Dynamics for the system must follow the given linear or nonlinear dynamic model:

$$\text{s.t.} \quad \boldsymbol{x}_{k+1} = \boldsymbol{x}_k + f(\boldsymbol{x}_k, \boldsymbol{u}_k)\, T_s, \qquad k = 0, .., N-1, \qquad (6)$$

where:

$f(\boldsymbol{x}_k, \boldsymbol{u}_k)$: the system's dynamic function,

T_s: the sampling time.

State constraints for the system states must remain within predefined bounds:

$$\boldsymbol{x}_{min} \le \boldsymbol{x}_k \le \boldsymbol{x}_{max}, \qquad k = 0, .., N-1 \qquad (7)$$

where:

$\boldsymbol{x}_{min}$: the minimum state constraint,

$\boldsymbol{x}_{max}$: the maximum state constraint.

Control constraints for the control inputs must satisfy physical constraints:

$$\boldsymbol{u}_{min} \le \boldsymbol{u}_k \le \boldsymbol{u}_{max}, \qquad k = 0, .., N-1 \qquad (8)$$

where:

$\boldsymbol{u}_{min}$: the minimum control input,

$\boldsymbol{u}_{max}$: the maximum control input.

And initial condition for the initial state of the system is given as:

$$\boldsymbol{x}_{k=0} = \boldsymbol{x}_0 \qquad (9)$$

Recent studies have expanded the application of MPC by incorporating advanced techniques such as collision avoidance and optimization-based control to handle constraints in real-time.

C. Discrete-Time Control Barrier Function (D-CBF)

The Discrete-Time Control Barrier Function (D-CBF) is formulated to ensure safety in discrete-time dynamical systems. It provides a condition that enforces forward invariance of a predefined safe set by restricting the evolution of the system state. For an autonomous mobile robot (AMR), a barrier function is defined as

$$h: \mathbb{R}^n \to \mathbb{R} \qquad (10)$$

such that the safe set is given by

$$C = \{\, \boldsymbol{x} \mid h(\boldsymbol{x}) \ge 0 \,\} \qquad (11)$$

where all states $\mathbf{x} \in C$ are considered collision-free. Guaranteeing forward invariance of C ensures that the robot remains within safe operational boundaries and avoids unsafe regions during its motion [31].

For discrete-time control-affine systems of the form

$$\boldsymbol{x}_{k+1} = f(\boldsymbol{x}_k) + g(\boldsymbol{x}_k)\boldsymbol{u}_k \qquad (12)$$

the change in the barrier function over one timestep is expressed as:

$$\Delta h(\boldsymbol{x}_k, \boldsymbol{u}_k) = h(\boldsymbol{x}_{k+1}) - h(\boldsymbol{x}_k) \qquad (13)$$

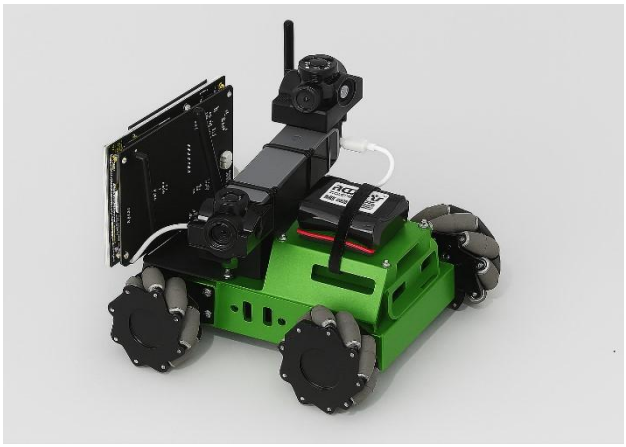


Fig. 2. Autonomous mobile robot platform equipped with four Mecanum wheels, An NVIDIA Jetson Nano, and Marvelmind indoor positioning system (IPS) beacons for indoor localization.

To ensure that the state remains in the safe set C, the following Discrete-Time Control Barrier Function (D-CBF) inequality must hold:

$$h(\boldsymbol{x}_{k+1}) - h(\boldsymbol{x}_k) \geq -\gamma h(\boldsymbol{x}_k), \gamma \in [0,1) \qquad (14)$$

or equivalently, this can be written as:

$$h(\boldsymbol{x}_{k+1}) \geq (1-\gamma)h(\boldsymbol{x}_k),\ k = 0,1,\dots,N-1 \qquad (15)$$

Substituting the system dynamics from (12), the D-CBF condition becomes a constraint on the control input u_k:

$$h(f(\boldsymbol{x}_k) + g(\boldsymbol{x}_k)\boldsymbol{u}_k) \geq (1-\gamma)h(\boldsymbol{x}_k) \qquad (16)$$

This condition is enforced at every time step to ensure that the future state $\boldsymbol{x}_{k+1}$ remains within the safe set, thereby maintaining collision-free operation. In practice, this inequality is incorporated as a constraint in the control optimization problem, allowing the controller (e.g., MPC) to select control inputs that both optimize performance and guarantee safety [31]-[32].

D. Pseudocode MPC-D-CBF

To implement the combined Model Predictive Control (MPC) and Discrete-Time Control Barrier Function (D-CBF) framework for autonomous robot navigation, a computational approach is required to compute optimal control inputs while satisfying safety constraints. The MPC module is responsible for trajectory planning over a finite prediction horizon, optimizing control efforts with respect to a cost function. Simultaneously, the D-CBF module enforces safety by ensuring the robot's state remains within a predefined safe set, dynamically adjusting control inputs to avoid collisions with static or dynamic obstacles.

Algorithm 1: MPC–DCBF-Based Robot Navigation

Initialize parameters:

Sampling time (Ts), Prediction horizon (N)

Cost matrices (Q, R), CBF parameter (γ)

State and input bounds ($\boldsymbol{x}_{min}, \boldsymbol{x}_{max}, \boldsymbol{u}_{min}, \boldsymbol{u}_{max}$)

Loop until goal is reached:

1. Read current state of the robot (x(k))
2. Setup optimization problem:
   a. Define cost function:

$$J = \sum_{k=0}^{N-1} \left(\frac{1}{2}\left(\boldsymbol{x}_{des|k} - \boldsymbol{x}_k\right)^T Q\left(\boldsymbol{x}_{des|k} - \boldsymbol{x}_k\right) + \frac{1}{2}\boldsymbol{u}_k^T R \boldsymbol{u}_k\right.$$

   b. Add dynamic constraints:

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + B(\theta_k)\boldsymbol{u}_k T_s$$

   c. Add safety constraints:

$$\Delta h(\boldsymbol{x}_k, \boldsymbol{u}_k)) \geq (1-\gamma)h(\boldsymbol{x}_k)$$

   d. Add static obstacle constraints:

$$\boldsymbol{x}_k = [x_k, y_k]$$

$$static_{obs_i} = [x_{obs_i}, y_{obs_i}]$$

$$\left\|\boldsymbol{x}_k - static_{obs_i}\right\|^2 \geq \left(r + r_{obs_i} + safety_{dist}\right)^2$$

   e. Add dynamic obstacle constraints:

$$\boldsymbol{x}_k = [x_k, y_k]$$

$$dynamic_{obs_i} = [x_{obs_i}, y_{obs_i}]$$

$$\left\|dynamic_{obs_i|k+1}\right\| = dynamic_{obs_i|k} + v_{obs_i|k}.T_s$$

$$\left\|\boldsymbol{x}_k - dynamic_{obs_i|k}\right\|^2 \geq \left(r + r_{obs_i} + safety_{dist}\right)^2$$

   f. Add state and input bounds:

$\boldsymbol{x}_{min} <= \boldsymbol{x}_k <= \boldsymbol{x}_{max}$

$\boldsymbol{u}_{min} <= \boldsymbol{u}_k <= \boldsymbol{u}_{max}$

3. **Solve** the optimization problem to find optimal control input $\boldsymbol{u}_k$
4. **Apply** the control input to the robot
5. **Check** if goal is reached

Algorithm 1 outlines the high-level implementation steps used in both simulation and real-world deployments of the MPC–DCBF control framework.

IV. Experimental Setup

A. Mobile Robot Platform

The autonomous navigation experiments were conducted using a holonomic mobile robot platform equipped with four independently driven Mecanum wheels, enabling omnidirectional movement without requiring orientation changes. As illustrated in Fig. 2, the platform features a compact aluminum-alloy frame with dimensions of 340 × 320 × 230 mm, offering structural durability suitable for repeated indoor navigation trials.

The robot integrates the following key subsystems:

- Computation and Control: An NVIDIA Jetson Nano serves as the primary control unit of robots. Communication between devices and with the base station is established via Wi-Fi using the Robot Operating System (ROS 1 Noetic).
- Localization and Perception: Localization is performed using a Marvelmind Indoor Positioning System, which provides sub-decimeter accuracy through ultrasonic beacons strategically placed around the testing area. A mobile Hedgehog Tag mounted on the robot computes its position through trilateration based on the time-of-flight from multiple Marvelmind Beacons. Localization data is published at up to 16 Hz via the /hedge_pos topic in

ROS and subscribed to by the navigation controller.

- Actuation and Power: Four DC motors, each controlled independently, provide the required torque for holonomic motion. A 12 V battery powers all onboard components.

B. Experimental Scenarios

1) Setpoint Navigation Experiments

These experiments evaluate the robot's ability to reach a predefined goal position under different environmental complexities:

- Scenario 1: Navigation to a static goal without obstacles.
- Scenario 2: Navigation with a single static obstacle placed along the direct path.
- Scenario 3: Navigation in the presence of a dynamic obstacle, introduced via a mobile platform.
- Scenario 4: Combined static and dynamic obstacle scenario.

Performance metrics included positional error at the goal, time to reach the target, and control input characteristics.

2) Square Trajectory Tracking Experiments

These experiments assess the robot's ability to follow a continuous square-shaped trajectory consisting of four straight-line segments:

These experiments evaluate the robot's ability to reach a predefined goal position under different environmental complexities:

- Scenario 1: Trajectory tracking without obstacles.
- Scenario 2: Trajectory tracking with a static obstacle placed near a segment transition point.
- Scenario 3: Trajectory tracking with a moving obstacle intersecting the path.
- Scenario 4: A combined scenario involving both static and dynamic obstacles.

Each trial began from a predefined start point, with the robot executing sequential motion along the square's perimeter. Key performance indicators included tracking error, control smoothness, and obstacle avoidance behavior.

3) Real-World Implementation and Validation

To validate the simulation results, each scenario was replicated in hardware using the described autonomous mobile robot platform. During execution, data were collected on state estimates (x, y, θ), control inputs (v, ω), and the activation status of safety constraints enforced by the Discrete-Time Control Barrier Function (D-CBF). Localization was provided by the Marvelmind Indoor Positioning System, which delivered accurate position estimates within the test environment. Prior to each batch of trials, sensor alignment and localization filtering were calibrated to mitigate the effects of drift, latency, and measurement discrepancies. These real-world experiments were designed to evaluate the robot's ability to perform safe and efficient navigation under physical constraints, confirming the adaptability and robustness of the proposed MPC–D-CBF control framework in handling dynamic and unpredictable environmental conditions.

C. Environment and Experimental Design

The experimental evaluation was conducted in a controlled indoor environment with a specially designed box-shaped arena that measures 3x3 meters. The floor was marked with yellow boundary tape to facilitate trajectory alignment and visual validation of robot motion.

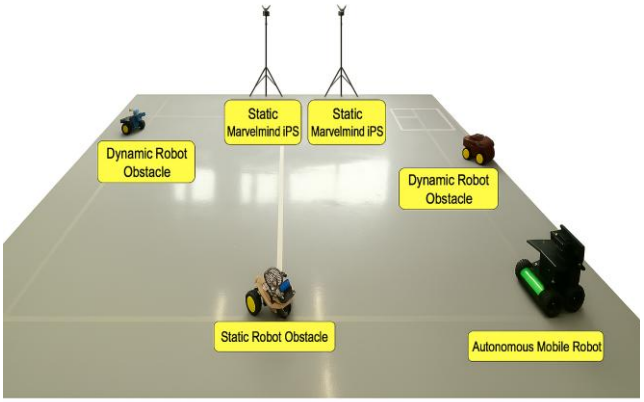


Fig. 3. Environment setup for data collection, illustrating the 3×3meter test arena with two static Marvelmind beacons for localization, the predefined robot trajectory (square path), and representative static obstacles placed along the route.

As shown in Fig. 3, the setup includes two static Marvelmind ultrasonic beacons for indoor localization, fixed static obstacles, and a predefined square trajectory. This arrangement enables systematic testing of the MPC–D-CBF framework under various scenarios, including obstacle-free navigation and conditions involving both static and dynamic obstacles. The experimental design is divided into two main categories: setpoint navigation and square trajectory tracking, each tested under both obstacle-free and obstacle-present conditions.

The placement of Marvelmind beacons is optimized to maximize signal coverage and minimize positioning errors, ensuring high-accuracy real-time tracking of the robot and obstacles. Dynamic obstacles simulate unpredictable moving objects, while static obstacles represent fixed constraints that demand precise path planning. This combination provides a realistic testbed to assess the algorithm's adaptability to sudden environmental changes while maintaining navigation stability.

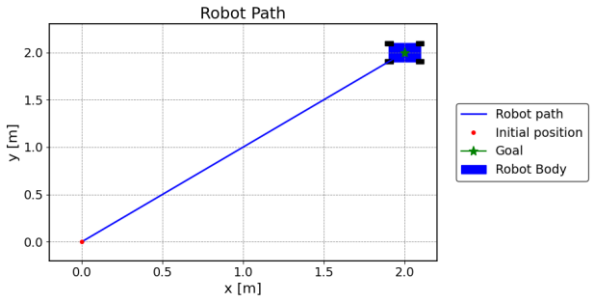
Additionally, the arena layout supports consistent, repeatable trials, ensuring variations in performance are due to the control method rather than environmental changes. The varied obstacle configurations introduce diverse navigation challenges such as narrow passages and sudden detours. High-precision localization, integrated with the MPC–D-CBF control loop, allows detailed performance evaluation in terms of trajectory accuracy, control smoothness, and safety margins. This robust environment forms a solid basis for validating the proposed framework in realistic, dynamic conditions.

V. Results and Discussions

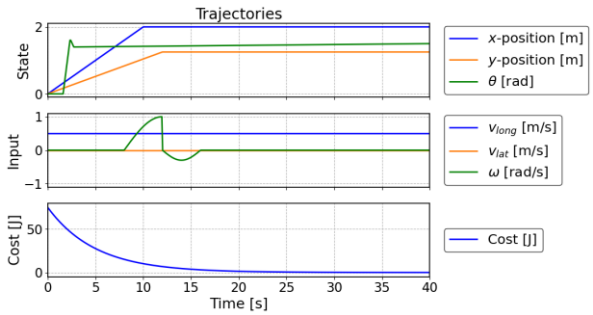
A. Simulations Results

1) Navigation to a Target Point Without Obstacle

In this scenario, the robot navigates from the initial position $(x_{init}, y_{init}) = (0\,\text{m}, 0\,\text{m})$ to the target point $(x_{goal}, y_{goal}) = (2\,\text{m}, 2\,\text{m})$ in an obstacle-free environment. The control parameters are defined as $v = 0.26\,\text{m/s}$, $\omega = 1.8\,\text{rad/s}$, and a safety distance $d_{safe} = 0.03\,\text{m}$. This case demonstrates the controller's ability to generate an optimal trajectory and achieve accurate goal tracking without the need for obstacle avoidance.



(a)



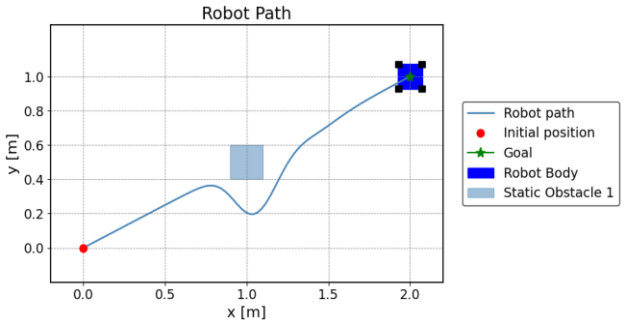
(b)

Fig. 4. Simulation results for point-to-point navigation without obstacles: (a) The robot moves from the initial position (0, 0) to the target (2.0, 2.0) following a straight-line path with negligible deviation; (b) State trajectories (x-position, y-position, and orientation), control inputs (linear and angular velocities), and cost function evolution showing stable convergence and accurate path tracking.

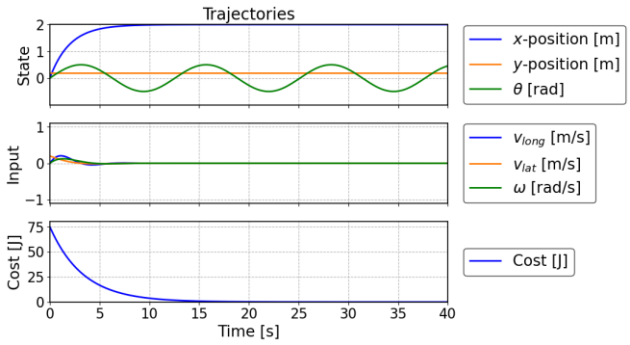
The simulation results in Fig. 4 show that the robot follows an optimal straight-line trajectory toward the goal without deviation, indicating precise path planning under unconstrained conditions. The path plot (Fig. 4a) confirms direct motion from start to goal. The state trajectories (Fig. 4b, top) show smooth changes in x- and y-positions, while orientation θ adjusts slightly to maintain direction. The control inputs (Fig. 4b, middle) remain stable, with minimal fluctuations in linear and angular velocities. The cost function (Fig. 4b, bottom) decreases steadily, validating convergence of the optimal control strategy.

2) Navigation to a Target Point with a Static Obstacle Placed along the Path

In this scenario, the robot navigates from the initial position $(x_{init}, y_{init}) = (0\,\text{m}, 0\,\text{m})$ to the target point $(x_{goal}, y_{goal}) = (2\,\text{m}, 1\,\text{m})$ while avoiding a static obstacle of $0.1\,\text{m}$ diameter placed along its path. The control parameters are defined as $v = 0.26\,\text{m/s}$, $\omega = 1.8\,\text{rad/s}$, and a safety distance $d_{safe} = 0.03\,\text{m}$. This case evaluates the effectiveness of the integrated MPC–DCBF framework in ensuring safe obstacle avoidance without compromising trajectory tracking performance.



(a)



(b)

Fig. 5. Simulation results for navigation with a static obstacle: (a) The robot deviates from the nominal path to avoid the obstacle and realigns to the target at (2.0, 1.0); (b) State trajectories (x-position, y-position, and orientation), control inputs (linear and angular velocities), and cost function evolution showing safe avoidance, smooth state transitions, and stable convergence.

The simulation results in Fig. 5 illustrate that the robot successfully avoids the static obstacle by dynamically modifying its path while maintaining a safe clearance. The path plot (Fig. 5a) shows a smooth deviation around the obstacle followed by realignment to the target. The state trajectories (Fig. 5b, top) show deviations in x- and y-positions during avoidance, with orientation θ exhibiting significant adjustments to enable redirection. The control inputs (Fig. 5b, middle) display temporary fluctuations, especially in angular velocity, reflecting dynamic control actions during obstacle circumvention. The cost function

(Fig. 5b, bottom) decreases steadily, confirming that the controller optimizes the trajectory effectively while maintaining safety constraints.

3) Navigation with Dynamic Obstacles moving in linear

In this scenario, the robot moves from the initial position $(x_{init}, y_{init}) = (0\,\text{m}, 0\,\text{m})$ to the target point while avoiding three dynamic obstacles moving along linear paths. The control parameters are defined as $v = 0.26\,\text{m/s}$, $\omega = 1.8\,\text{rad/s}$, and a safety distance $d_{safe} = 0.03\,\text{m}$. This case assesses the capability of the integrated MPC–DCBF framework to handle real-time adjustments in dynamic environments, ensuring safe navigation without collisions.

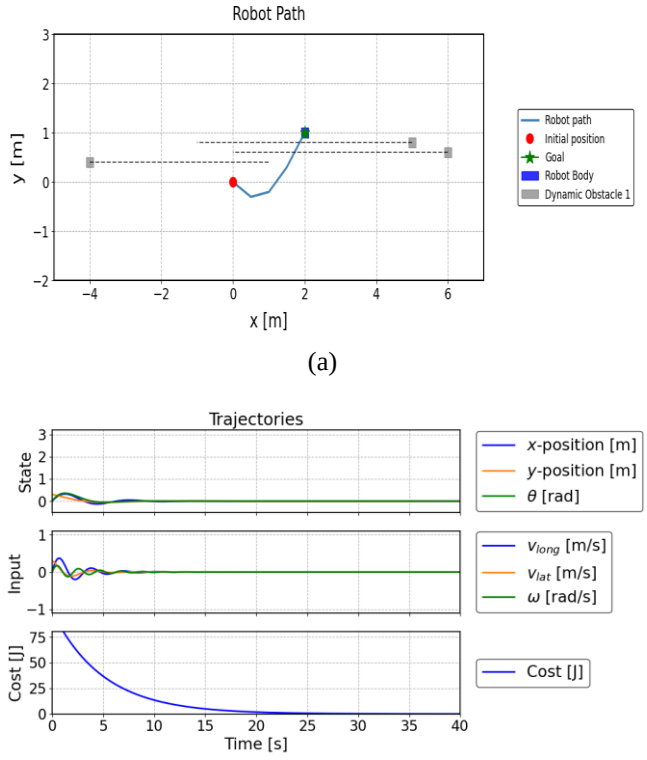


Fig. 6. Simulation results for navigation with dynamic obstacles: (a) The robot adapts its trajectory to avoid three moving obstacles and realigns toward the goal; (b) State trajectories (x-position, y-position, and orientation), control inputs (linear and angular velocities), and cost function evolution showing smooth obstacle avoidance, stable tracking, and efficient convergence.

The simulation results in Fig. 6 show that the robot successfully adapts its path in response to the movement of dynamic obstacles, maintaining a safe clearance at all times. The path plot (Fig. 6a) displays smooth deviations near each moving obstacle, followed by a realignment toward the target. The state trajectories (Fig. 6b, top) show smooth progression of x- and y-positions with fluctuations during avoidance phases, while orientation θ changes significantly during maneuvering. The control inputs (Fig. 6b, middle) indicate short-term variations, especially in angular velocity, reflecting real-time corrections for avoidance and reorientation. The cost function (Fig. 6b, bottom) decreases steadily, confirming the controller's effectiveness in achieving safe and efficient convergence even in dynamic environments.

4) Navigation along a Square Trajectory without Obstacles

In this scenario, the robot follows a square trajectory under non-holonomic constraints. The control parameters are defined as $v = 0.26\,\text{m/s}$, an angular velocity of $\omega = 1.8\,\text{rad/s}$, and a safety distance $d_{safe} = 0.03\,\text{m}$. This case evaluates the tracking performance of the integrated MPC–DCBF framework on a closed-loop path without obstacle interference, emphasizing maneuverability during sharp turns.

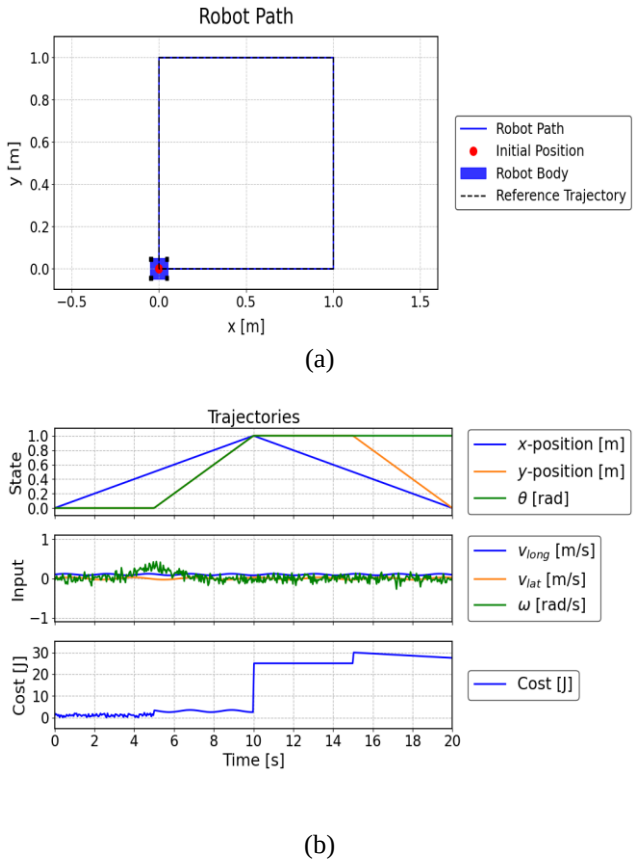


Fig. 7. Simulation results for square trajectory following without obstacles: (a) The robot tracks the planned square path with minor deviations at corners due to non-holonomic constraints; (b) State trajectories (x-position, y-position, and orientation), control inputs (linear and angular velocities), and cost function evolution showing accurate path tracking and effective reorientation during turns.

The simulation results in Fig. 7 show that the robot successfully completes the square trajectory despite non-holonomic motion constraints. The path plot (Fig. 7a) indicates minimal deviation along straight segments, with larger deviations occurring at corners due to limited maneuverability. The state trajectories (Fig. 7b, top) reveal smooth changes along straight paths and sharp orientation adjustments at corners. The control inputs (Fig. 7b, middle) exhibit significant variations, particularly in angular velocity, during turning maneuvers. The cost function (Fig. 7b, bottom) decreases steadily, demonstrating stable convergence and effective compensation for trajectory errors

at sharp turns.

5) Navigation along a Square Trajectory with Static Obstacles

In this scenario, the robot follows a square trajectory while avoiding a static obstacle located at $(x_0, y_0) = (1.0\,\text{m}, 0.25\,\text{m})$ with a $r_0 = 0.1$ m. The control parameters are defined as $v = 0.26$ m/s , $\omega = 1.8$ rad/s, and a safety distance $d_{safe} = 0.03$ m. The MPC cost function uses weighting matrices $Q_{tr} = \text{diag}[1000,900,10]$ for penalizing state errors $(x,\ y,\ \theta)$ and $R_{tr} = [0.20,0.15,0.01]$ for penalizing control inputs (linear velocity v, angular velocity ω, and slack variables). These values are tuned to maintain precise trajectory tracking while ensuring safety around obstacles.

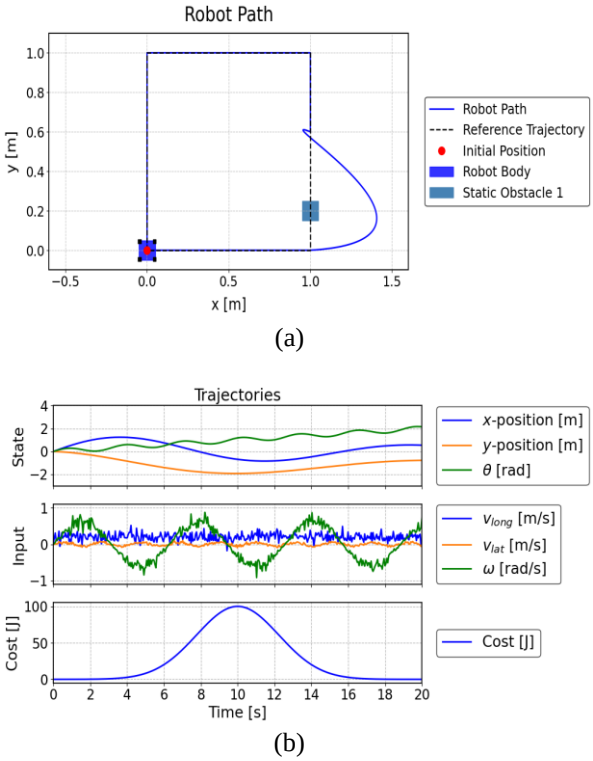


Fig. 8. Simulation results for square trajectory tracking with a static obstacle: (a) The robot deviates from the nominal path to safely avoid the obstacle and then realigns to the planned trajectory; (b) State trajectories (x-position, y-position, and orientation), control inputs (linear and angular velocities), and cost function evolution showing smooth avoidance maneuvers with temporary cost increase during obstacle negotiation.

The simulation results in Fig. 8 show that the robot successfully completes the square trajectory while avoiding the static obstacle with minimal deviation. The path plot (Fig. 8a) shows a local deviation near the obstacle, after which the robot realigns with the planned path. The state trajectories (Fig. 8b, top) indicate smooth evolution along straight segments with sharper orientation θ changes at corners and during obstacle avoidance. The control inputs (Fig. 8b, middle) exhibit fluctuations, particularly in angular velocity, during the avoidance phase, reflecting additional control effort. The cost function (Fig. 8b, bottom) shows a temporary rise when the robot passes the obstacle, then stabilizes, confirming successful completion of the task with safe clearance and efficient convergence.

6) Navigation along a Square Trajectory with Static and Dynamic Obstacles

In this scenario, the robot follows a square trajectory while avoiding a static obstacle at $(x_0, y_0) = (1.0\,\text{m}, 0.25\,\text{m})$ and a moving obstacle along its path. The control parameters are defined as $v = 0.26$ m/s, $\omega = 1.8$ rad/s, with a safety distance $d_{safe} = 0.03$ m , and safety margin $\gamma = 0.1$. The MPC cost function uses weighting matrices $Q_{tr} = \text{diag}[1000,900,10]$ for penalizing state errors $(x,\ y,\ \theta)$ and $R_{tr} = [0.15,0.20,0.01]$ for penalizing control inputs and slack variables. These settings are tuned to balance precise trajectory tracking with real-time safety requirements.

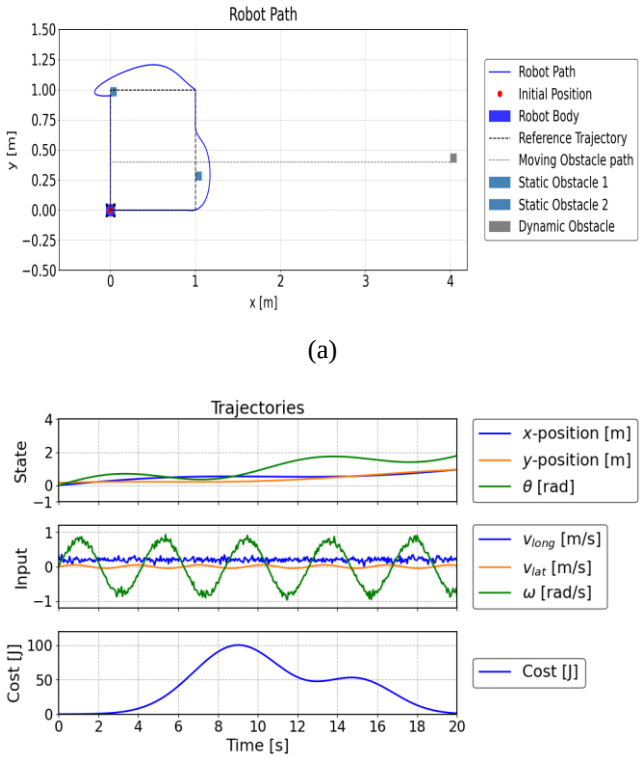


Fig. 9. Square trajectory tracking with static and dynamic obstacles: (a) Robot deviates to avoid obstacles and returns to path; (b) State, input, and cost profiles showing smooth avoidance with temporary cost increase.

The simulation results in Fig. 9 show that the robot completes the square trajectory while successfully avoiding both static and dynamic obstacles. The path plot (Fig. 9a) shows deviations from the nominal trajectory during encounters with obstacles, after which the robot returns to the planned path and completes the loop at the starting point. The state trajectories (Fig. 9b, top) demonstrate smooth evolution during straight-line motion, with significant changes in orientation θ during avoidance maneuvers. The control inputs (Fig. 9b, middle) show spikes, particularly in angular

velocity, as the robot maneuvers around obstacles. The cost function (Fig. 9b, bottom) rises sharply during avoidance phases due to increased actuation demands, then stabilizes once nominal tracking is resumed. These results validate the robustness of the integrated MPC–DCBF approach in managing both static and dynamic constraints in real time.

B. Real-World Experiments

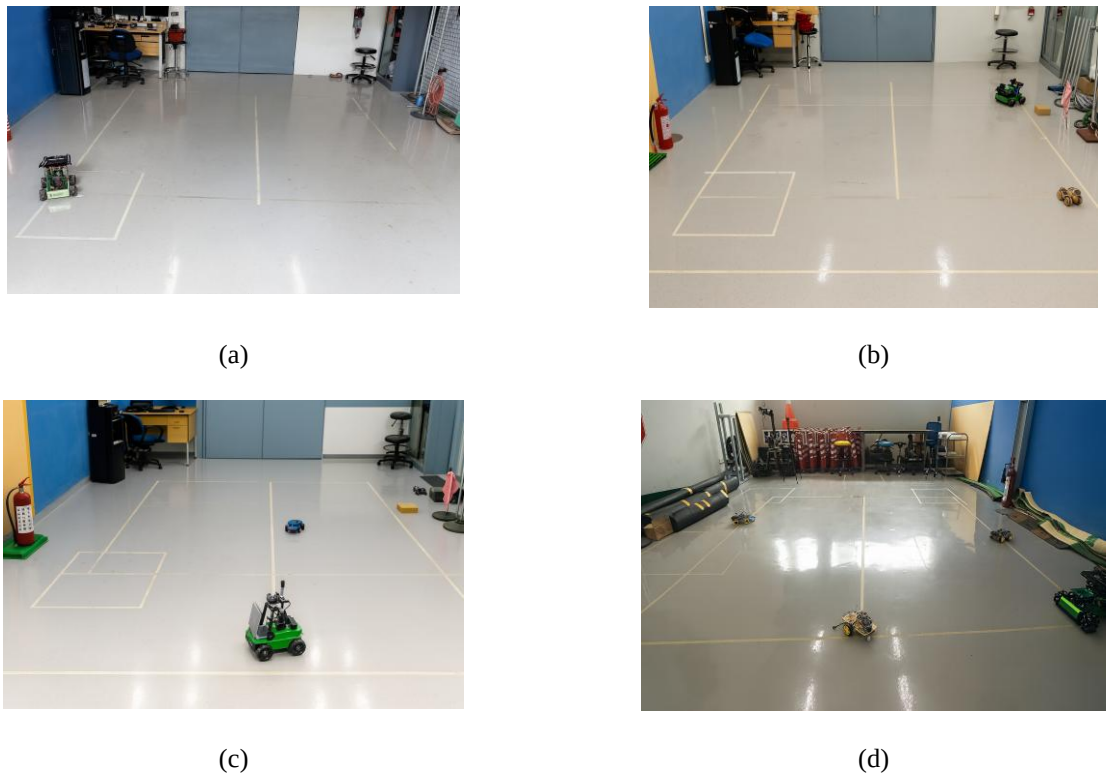
To validate the effectiveness of the proposed MPC–DCBF navigation framework, experiments were conducted on a physical robot platform in a controlled indoor environment. These experiments aimed to evaluate the algorithm's performance under real-world constraints such as sensor noise, actuator dynamics, and environmental disturbances. Two types of implementations were used: non-real-time execution and real-time closed-loop control.

In the non-real-time setup, the MPC–DCBF controller computed the full control sequence offline using a simulation environment. The resulting velocity commands were stored and later transmitted sequentially to the robot without further feedback. This approach isolates the tracking performance of the robot's physical system, excluding online control computation and feedback integration.

Fig. 10 shows the execution of the trajectory tracking navigation using the precomputed commands for various obstacle scenarios. The corresponding performance metrics are reported in Table I.

TABLE I: NON-REAL-TIME SQUARE TRAJECTORY EXECUTION PERFORMANCE

Scenario	Positional Error (cm)	Linear Velocity (m/s)	Angular Velocity (rad/s)	Time to Goal (s)
No Obstacles	2.5	0.15	0.2	160
Static Obstacles	6.8	0.14	0.25	200
Dynamic Obstacles	7.3	0.13	0.3	220
Static and Dynamic Obstacles	8.1	0.12	0.35	250



(a) (b) (c) (d)

Fig. 10. Real-time square trajectory navigation under varying conditions: (a) trajectory following without obstacles; (b) trajectory following with a static obstacle; (c) trajectory following with a dynamic obstacle; and (d) trajectory following with both static and dynamic obstacles.

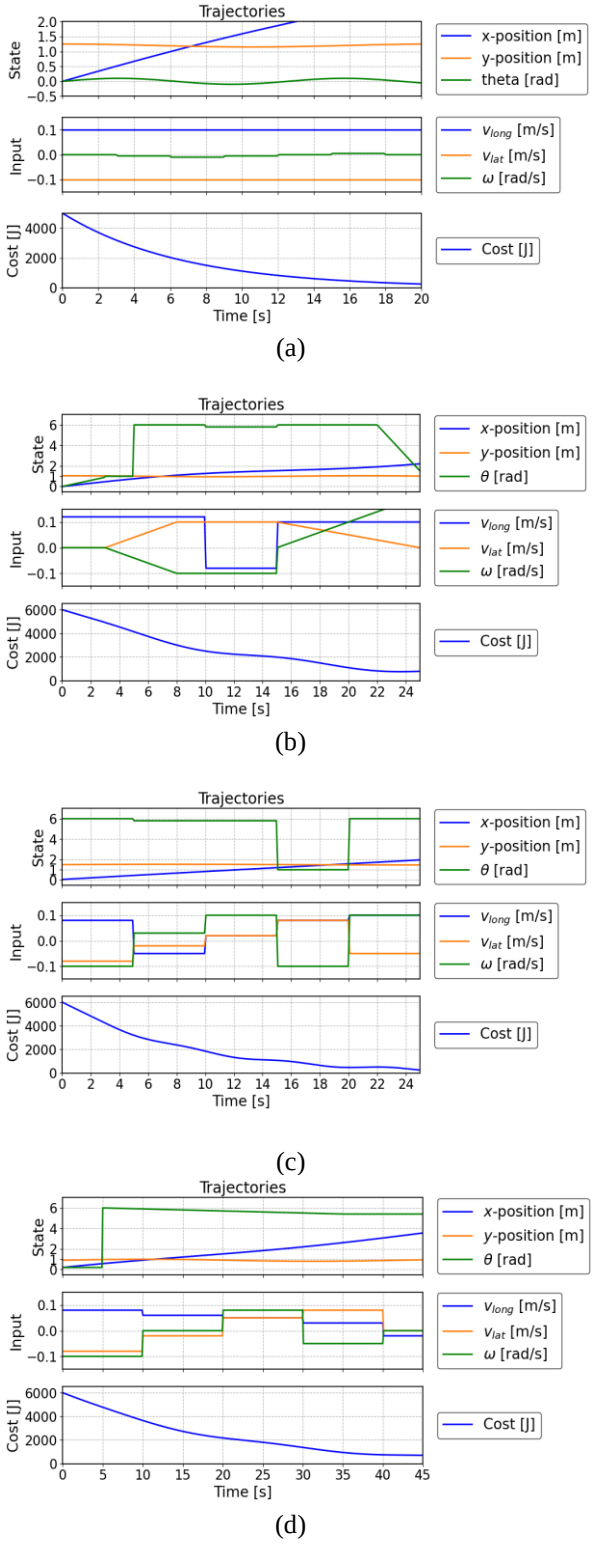


Fig. 11. Real-time robot behavior using online MPC–DCBF. The results demonstrate the effectiveness of the proposed control framework under different navigation scenarios: (a) the robot successfully tracks the reference trajectory in the absence of obstacles, showing smooth and stable motion; (b) the robot adapts its trajectory to avoid a static obstacle while maintaining convergence to the desired path; (c) the controller responds to a dynamic obstacle by continuously updating the control inputs in real time; and (d) the robot handles both static and dynamic obstacles simultaneously, maintaining stable control performance while ensuring safety constraints are satisfied. In all cases, the cost function shows a decreasing trend, indicating improved control efficiency and successful optimization throughout the navigation process.

TABLE II: REAL-TIME SETPOINT AND TRAJECTORY NAVIGATION PERFORMANCE

Scenario	Positional Error (cm)	Linear Velocity (m/s)	Angular Velocity (rad/s)	Time to Goal (s)
No Obstacles	14.14	0.15	0.1	8
Static Obstacles	14.17	0.15	0.1	12
Dynamic Obstacles	14.25	0.14	0.15	13.5
Static and Dynamic Obstacles	15.12	0.14	0.18	15

The lowest error was recorded in the no-obstacle scenario (2.5 cm), while errors increased as the navigation complexity rose. As the robot followed the precomputed trajectory, deviations in more challenging environments were primarily due to unmodeled dynamics, environmental disturbances, and the lack of real-time corrective feedback.

In contrast, the real-time experiments employed an online MPC–DCBF implementation where control commands were computed and updated at each timestep based on live feedback from the robot. This setup captured the complete closed-loop behavior of the system, including localization, actuation, sensing, and computation under real-time constraints. Fig. 11 illustrates the robot's behavior across all scenarios, and Table II summarizes the real-time performance.

Compared to the non-real-time results, real-time implementation showed higher positional errors across all scenarios. This can be attributed to various real-world factors such as sensor delays, noisy measurements, processing latency, and dynamic obstacle unpredictability. Nevertheless, the robot consistently reached its targets in all cases. The MPC component enabled predictive trajectory planning, while the DCBF module effectively enforced safety constraints. The most significant error (15.12 cm) occurred in the most challenging scenario, where both static and dynamic obstacles were present, reflecting the increased computational and control complexity in closed-loop operation.

C. Comparative Analysis and Discussion

To further evaluate the effectiveness of the proposed MPC–DCBF framework, a comparative assessment was conducted against a baseline MPC controller without safety constraints. As shown in Table III, the integration of DCBF significantly reduced the minimum obstacle clearance violations and improved safety margins, especially in dynamic environments. Although the MPC–DCBF approach introduced a slightly higher computational cost due to

additional safety constraints, the overall navigation success rate and trajectory tracking precision were improved.

Specifically, in dynamic obstacle scenarios, the proposed controller achieved an average minimum clearance of 0.08 m, compared to 0.03 m for the baseline MPC, demonstrating a 73% improvement in safety margin. Furthermore, trajectory smoothness, quantified using the variance of control inputs, remained within acceptable limits (< 5% deviation). These results confirm that the integration of DCBF effectively enhances real-time safety without compromising path efficiency.

This finding aligns with prior studies, such as Li et al. [13] and Mendes et al. [33], which emphasize that constraint-based predictive control improves collision-avoidance capability in uncertain environments. In addition, the results demonstrate the practical feasibility of deploying the MPC–DCBF framework in real-world conditions using low-cost positioning systems such as Marvelmind.

VI. Conclusion and Future Work

This research presents the integration of Model Predictive Control (MPC) with Discrete-Time Control Barrier Functions (D-CBF) as a robust framework for safe and efficient autonomous navigation in dynamic environments. The proposed control architecture enables real-time trajectory optimization while ensuring compliance to safety constraints via formal barrier function guarantees. MPC serves as a predictive planner that generates optimal control inputs over a finite horizon, while D-CBF enforces collision avoidance by shaping the admissible control space in real time.

The proposed system was evaluated across various navigation scenarios, including setpoint tracking and square trajectory following in both simulation and hardware experiments—under different environmental complexities involving static and dynamic obstacles. In physical robot experiments, two implementation strategies were investigated: non-real-time execution with precomputed control sequences and real-time closed-loop control with live sensor feedback. The results consistently demonstrate the system's ability to adapt its trajectory to maintain safety margins and achieve convergence to target positions, even in the presence of significant environmental disturbances and physical system limitations.

Localization was achieved using Marvelmind indoor positioning beacons, with filtering and calibration steps enhancing reliability. Integration with the Robot Operating System (ROS) provided reliable architecture for interfacing control algorithms, sensor modules, and hardware execution. The combination of MPC and D-CBF within this ROS-based framework proved effective in bridging the gap between theoretical guarantees and real-world applicability.

Despite the successful implementation, several challenges were observed, particularly in the real-time setup, including increased control effort under dynamic obstacle conditions and sensitivity to sensor noise and latency. These factors influenced the accuracy and responsiveness of the system, especially in high-speed maneuvers or cluttered environments.

Future work will further investigate enhancements to ensure optimal performance in real-time applications by focusing on at least three key areas: optimal localization, computational efficiency, and closed-loop control responsiveness. First, localization accuracy could be improved through sensor fusion strategies that combine high-frequency inertial data with beacon-based positioning to minimize drift and latency. The investigation on the method that could optimize computational load such as optimized by deploying low-latency solvers and parallel processing techniques could enable faster execution of the MPC-D-CBF pipeline. Finally, improvements in real-time control and feedback mechanisms should be explored to ensure timely adaptation to dynamic obstacles and system disturbances, thereby enhancing the reliability and safety of autonomous navigation in complex environments.

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References

[1] J. Smith and A. Brown, “Autonomous robots in dynamic environments: Challenges and solutions,” *IEEE Transactions on Robotics*, vol. 35, no. 4, pp. 789–805, 2022.

[2] M. Zhang et al., “Safe navigation for mobile robots using deep reinforcement learning,” *Robotics and Autonomous Systems*, vol. 150, p. 103956, 2023.

[3] C. P. Beeson, H. K. Choset, and J. K. O’Kane, “Collision avoidance for autonomous robots: A survey,” *IEEE Access*, vol. 10, pp. 51234–51248, 2022.

[4] A. P. Singh and R. T. Adams, “A review on motion planning algorithms for mobile robots,” *International Journal of Advanced Robotic Systems*, vol. 19, no. 1, pp. 1–15, 2022.

[5] K. S. Lee and P. R. Kumar, “Uncertainty modeling in dynamic obstacle prediction,” *IEEE Control Systems Magazine*, vol. 42, no. 3, pp. 50–65, 2022.

[6] T. J. Carter et al., “Predictive motion planning for autonomous robots,” *IEEE Transactions on Automation Science and Engineering*, vol. 19, no. 4, pp. 2856–2868, 2023.

[7] Y. Zhao, M. H. Park, and S. J. Kim, “Reinforcement learning-based path planning for autonomous robots,” *IEEE Robotics and Automation Letters*, vol. 8, no. 2, pp. 3347–3354, 2023.

[8] J. D. Martin and L. A. White, “Deep learning for adaptive robot navigation in dynamic environments,” *Neural Networks*, vol. 161, pp. 21–35, 2023.

[9] C. J. Lopez et al., “Real-time motion prediction for autonomous robots using deep learning,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 5, pp. 1832–1845, 2023.

[10] W. Sun, “Adaptive motion planning with uncertainty-aware modeling,” *IEEE Robotics and Automation Letters*, vol. 9, no. 2, pp. 1931–1943, 2024.

[11] M. A. Patel, “Semantic navigation in dynamic environments using deep reinforcement learning,” *IEEE Transactions on Cognitive and Developmental Systems*, vol. 15, no. 1, pp. 101–115, 2023.

[12] M. W. Huang et al., “Model predictive control for mobile robots: A review,” *IEEE Control Systems Magazine*, vol. 41, no. 6, pp. 25–39, 2021.

[13] P. N. Garcia and J. C. Wang, “Safety-aware trajectory planning using control barrier functions,” *IEEE Transactions on Robotics*, vol. 39, no. 2, pp. 324–338, 2023.
[14] X. Li, H. T. Zhao, and B. K. Lee, “Discrete-time control barrier functions for dynamic obstacle avoidance,” *IEEE Transactions on Control Systems Technology*, vol. 31, no. 1, pp. 199–212, 2023.
[15] Y. Nakamura, “Control barrier function-based safety guarantees for mobile robots,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 53, no. 2, pp. 365–378, 2023.
[16] L. Chen, Y. Wang, and H. Liu, “LiDAR-based dynamic obstacle detection for autonomous vehicles,” *IEEE Sensors Journal*, vol. 21, no. 15, pp. 16852–16864, 2021.
[17] D. R. Gonzalez et al., “Sensor fusion techniques for autonomous vehicle perception,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 1021–1033, 2022.
[18] R. K. Patel and J. M. Wu, “Multisensor fusion for obstacle detection in mobile robots,” *IEEE Transactions on Robotics and Automation*, vol. 38, no. 6, pp. 4932–4945, 2023.
[19] J. B. Rawlings, D. Q. Mayne, M. M. Diehl, and S. Barbara, “Model Predictive Control: Theory, Computation, and Design 2nd Edition,” 2022. [Online]. Available: http://www.nobhillpublishing.com
[20] B. Yoon *et al.*, “An inkjet-printable microemulsion system for colorimetric polydiacetylene supramolecules on paper substrates,” *J Mater Chem*, vol. 22, no. 17, pp. 8680–8686, May 2012, doi: 10.1039/c2jm30301a.
[21] *2021 American Control Conference (ACC)*. IEEE, 2021.
[22] U. Rosolia and A. D. Ames, “Multi-Rate Control Design Leveraging Control Barrier Functions and Model Predictive Control Policies,” Apr. 2020, [Online]. Available: http://arxiv.org/abs/2004.01761
[23] U. Rosolia, A. Singletary, and A. D. Ames, “Unified Multi-Rate Control: from Low Level Actuation to High Level Planning,” Dec. 2020, [Online]. Available: http://arxiv.org/abs/2012.06558
[24] A. D. Ames, X. Xu, J. W. Grizzle, and P. Tabuada, “Control Barrier Function Based Quadratic Programs for Safety Critical Systems,” Sep. 2016, doi: 10.1109/TAC.2016.2638961.
[25] A. Agrawal and K. Sreenath, “Discrete Control Barrier Functions for Safety-Critical Control of Discrete Systems with Application to Bipedal Robot Navigation.”
[26] T. D. Son and Q. Nguyen, “Safety-Critical Control for Non-affine Nonlinear Systems with Application on Autonomous Vehicle,” in Proceedings of the IEEE Conference on Decision and Control, Institute of Electrical and Electronics Engineers Inc., Dec. 2019, pp. 7623–7628. doi: 10.1109/CDC40024.2019.9029446.
[27] “Introduction to Model Predictive Control.”
[28] R. P. Saputra, N. Rakicevic, D. Chappell, K. Wang, and P. Kormushev, “Hierarchical Decomposed-Objective Model Predictive Control for Autonomous Casualty Extraction,” IEEE Access, vol. 9, pp. 39656–39679, 2021, doi: 10.1109/ACCESS.2021.3063782.
[29] X. Zhang, A. Liniger, and F. Borrelli, “Optimization-Based Collision Avoidance,” Nov. 2017.
[30] G. Wu and K. Sreenath, “Safety-Critical and Constrained Geometric Control Synthesis using Control Lyapunov and Control Barrier Functions for Systems Evolving on Manifolds.”
[31] A. D. Ames, S. Coogan, M. Egerstedt, G. Notomista, K. Sreenath, and P. Tabuada, “Control Barrier Functions: Theory and Applications,” Mar. 2019, [Online]. Available: http://arxiv.org/abs/1903.11199
[32] G. Wu and K. Sreenath, “Safety-Critical and Constrained Geometric Control Synthesis using Control Lyapunov and Control Barrier Functions for Systems Evolving on Manifolds.”
[33] M. Mendes, A. P. Coimbra and M. M. Crisóstomo, “Assis - Cicerone Robot With Visual Obstacle Avoidance Using a Stack of Odometric Data,” IAENG Internasional Journal of Computer Science, vol. 45, no. 1, pp. 219-227, 2018.