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Adaptive Control of Autonomous Mobile Robots Using Fuzzy Logic-Based PID Optimization

Sofia Almeida*[1], Michael Chen[2]
Email: sofia_almeida_utoronto@gmail.com
[1,2]*University of Toronto, Toronto, Canada*
*Corresponding Author

Abstract

Autonomous mobile robots require precise navigation and stability in dynamic environments, where traditional control methods often fail to balance accuracy, responsiveness, and robustness. This study proposes an adaptive fuzzy–PID control framework to optimize real-time trajectory tracking and disturbance rejection. The approach integrates a fuzzy inference system with adaptive proportional integral–derivative (PID) gain tuning, enabling continuous adjustment of control parameters based on instantaneous tracking error and error rate. The methodology combines MATLAB/Simulink and ROS Gazebo simulations with physical experiments on a differential-drive mobile robot equipped with LiDAR, inertial sensors, and high-resolution wheel encoders. Results demonstrate that the adaptive fuzzy–PID controller reduced overshoot by 42%, shortened settling time by 35%, and maintained a steady-state lateral error below 1 cm and heading deviation under 0.5°, outperforming classical PID and conventional fuzzy-PID schemes. These findings confirm robust adaptation to nonlinear dynamics and unexpected disturbances without significant computational overhead. The proposed framework emphasizes interpretability and practical applicability, providing insights for multi-robot coordination, self-driving vehicles, and industrial or service robotics where reliability and safety are critical.

Keywords: *Fuzzy Logic, Adaptive Control, PID Optimization, Mobile Robotics, Navigation Stability.*

I. INTRODUCTION

Autonomous mobile robotics have progressed from experimental platforms to essential systems in industrial, healthcare, and service applications, particularly for navigating unstructured and dynamic environments while maintaining stability (Alatise & Hancke, 2020; Niloy et al., 2021). Despite these advances, ensuring consistent navigation and robust motion control remains challenging, especially in environments with unpredictable obstacles, changing terrain, or sensor noise. The classic proportional–integral–derivative (PID) controller is popular due to its robustness and simplicity, but often demonstrates reduced tracking performance under nonlinear dynamics or external disturbances (Guo et al., 2021; Oladipo et al., 2020). This challenge motivates the development of control approaches capable of online adaptation to maintain stability and performance.

Over the past decade, research has explored multiple avenues to improve the agility and resilience of autonomous mobile robots. Sensor fusion enhances perception and localization, yet control layers still limit overall performance (El-Sheimy & Youssef, 2020; Petrlik et al., 2021). Fuzzy logic controllers enable human-like reasoning under uncertainty, but static rule bases can fail when environmental conditions change significantly (Mittal et al., 2020; Wu & Xu, 2021). Standalone adaptive methods can operate efficiently at runtime but often struggle with

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convergence or impose high computational demands, which is critical for resource-limited mobile platforms (Annaswamy & Fradkov, 2021; Lopez & Slotine, 2021). The remaining gap between fuzzy inference adaptability and PID stability motivates the hybridization into an adaptive fuzzy-PID framework.

The adaptive fuzzy-PID control framework proposed in this study directly addresses these limitations by integrating nonlinear reasoning of fuzzy logic with the proven stability of PID control. Unlike traditional controllers that rely on offline tuning, the proposed controller continuously adjusts PID gains using fuzzy inference to handle non-steady-state dynamics in real time (Bo et al., 2021; Fu et al., 2022). Prior studies have demonstrated that this hybrid approach improves transient response and reduces overshoot in various applications, from magnetic bearing systems to pH control (Benzian et al., 2021; Mughees & Mohsin, 2020). Applying this concept to mobile robots presents an opportunity to enhance trajectory tracking, reduce energy consumption, and improve stability across operational modes.

Recent advancements in robotics further highlight the relevance of this study. Mobile platforms are increasingly deployed for precision agriculture, search and rescue, and other tasks requiring mobility and reliability (Galati et al., 2022; Rovira-Mas et al., 2021). While reinforcement learning and deep neural methods have gained popularity for planning and routing (Garaffa et al., 2023; Zhu & Zhang, 2021) , they often require extensive training data and computational resources beyond the capacity of lightweight robots. In contrast, adaptive fuzzy–PID control balances intelligent adaptability with moderate computational demands, making it suitable for embedded systems requiring responsive control (Duan, 2021; Fan et al., 2021).

The objective of this study is to design, implement, and evaluate an adaptive fuzzy-PID controller that improves the navigation and stability of autonomous mobile robots in the presence of real-world uncertainties. Our contributions are threefold. First, we propose a controller architecture that combines fuzzy-logic-based adaptation with continuous PID gain optimization to address nonlinearities and disturbances. Second, we validate this architecture in high-fidelity simulations and real-world experiments to capture practical constraints. Third, we demonstrate superior performance compared to classical PID and conventional fuzzy controllers, showing improvements in overshoot, settling time, and trajectory accuracy (Berkane, 2020; Sánchez-Ibáñez et al., 2021). These contributions bridge theoretical control design and deployable solutions for autonomous robotics.

The remainder of this manuscript is structured to provide a clear progression for the reader. Chapter 2 reviews developments in control algorithms for autonomous mobile robots and highlights the limitations of traditional PID and fuzzy controllers. Chapter 3 details the adaptive fuzzy-PID approach, including controller design, fuzzy inference framework, and real-time parameter adaptation. Chapter 4 presents simulation and experimental setups to validate performance. Chapter 5 discusses results, including navigation accuracy, stability measures, and energy consumption. Finally, Chapter 6 summarizes findings and outlines future research directions, such as integrating advanced mapping techniques or multi-robot coordination (Arduengo et al., 2021; M, 2020). Overall, this study demonstrates that combining adaptive control with fuzzy logic enhances robustness and performance in practical, uncertain environments.

II. LITERATURE REVIEW

Topics in reinforcement learning, fuzzy control, and robot navigation have been widely investigated due to their contributions to the development of intelligent robotic systems. The area of adaptation has supported frameworks that manage uncertainty in nonlinear dynamics (Annaswamy & Fradkov, 2021; Lopez & Slotine, 2021). Recently, the scope of adaptation has expanded into reinforcement learning, providing robotics solutions that incorporate safety considerations in complex environments (Fan et al., 2021; Garaffa et al., 2023). Reinforcement learning approaches have also been applied to intelligent sensing with full-state constraints and integral barrier Lyapunov functions (Liu et al., 2020, 2021). These studies indicate a trend toward hybrid approaches that combine formal control theory with data-driven learning to enable mobile robots to operate under nonstationary and uncertain conditions.

Fuzzy-PID controllers are a significant research area, enabling heuristics to enhance traditional feedback control and to manage nonlinear or time-varying systems. Optimization methods such as particle swarm optimization (PSO) and fractional-order specifications have further increased the flexibility and practical applicability of fuzzy-PID controllers (Bo et al., 2021; Guo et al., 2021). Despite these advances, many fuzzy-PID approaches remain static or tuned offline, limiting their performance in dynamic, noisy, or uncertain environments. Applications range from magnetic bearing systems to biomedical control, such as type-1 diabetes regulation (Benzian et al., 2021) and pH regulation in water fertilization (Fu et al., 2022). Recent integration with metaheuristic optimization shows potential for reduced overshoot and faster transient response in robotics, but critical evaluation in real-world robotic navigation remains limited (Esleman et al., 2021; Mughees & Mohsin, 2020).

Mobile robot navigation serves as the operational context for both adaptive control and fuzzy-PID strategies. Navigation in unstructured and dynamic environments remains challenging (Alatise & Hancke, 2020; Niloy et al., 2021; Sánchez-Ibáñez et al., 2021). Approaches vary from safety velocity cones for unknown terrain (Berkane, 2020), to particle-filtered localization for high-accuracy navigation (Rupeng et al., 2021). Sensor fusion techniques that integrate LiDAR and inertial measurements enhance reliability under limited visibility or GPS-denied conditions (El-Sheimy & Youssef, 2020; Petrlik et al., 2021). Deep reinforcement learning has recently demonstrated feasibility for autonomous planning (Wen et al., 2021; Zhu & Zhang, 2021). However, computational demands often exceed the capabilities of embedded robotic platforms, highlighting the need for efficient, adaptive solutions.

The interdependence between adaptive control, fuzzy-PID, and mobile navigation becomes clear when evaluating practical robotic applications. Robust operation in cluttered indoor environments (Arduengo et al., 2021) or precise navigation in agricultural fields (Rovira-Mas et al., 2021) benefits from adaptive algorithms enhanced with fuzzy inference to handle uncertainty. Mobile robots are increasingly applied to industrial and experimental tasks, illustrating vast socio-technical potential (Burger et al., 2020; Galati et al., 2022). Furthermore, incorporating AI-driven sensing and modern communication technologies, from adaptive radar to IoT-based monitoring (Ghofur & Riyanto, 2025; Ibrahim et al., 2024) provides additional justification for integrating fuzzy-PID with PSO optimization on ROS–Gazebo simulation platforms to balance computational efficiency, adaptability, and real-world applicability. A comparative overview of these approaches is presented in Table 1 to highlight each method's specific contributions.

Table 1. Comparative Summary of Representative Approaches in Adaptive Control, Fuzzy-PID, and Mobile Robot Navigation

Approach & Key References	Main Contribution to Dynamic Performance	Computational Complexity	Notable Application Domain
Adaptive Control (Annaswamy & Fradkov, 2021; Fan et al., 2021; Liu et al., 2021)	Ensures stability under parametric uncertainty; enables safety-critical adaptation	Moderate to high, depending on state constraint handling	Nonlinear robotic systems, safety-critical UAVs
Fuzzy-PID (Bo et al., 2021; Fu et al., 2022; Mughees & Mohsin, 2020)	Reduces overshoot and improves transient response in nonlinear plants	Moderate due to heuristic rule-based and optimization	Magnetic bearing systems, biomedical control
Mobile Robot Navigation (Alatise & Hancke, 2020; Petrlik et al., 2021; Zhu & Zhang, 2021)	Enhances autonomous path planning and localization in unstructured environments	High when integrating multi-sensor fusion and deep learning	Indoor/outdoor autonomous robots, industrial logistics

Table 1 summarizes representative approaches across adaptive control, fuzzy-PID, and mobile robot navigation, highlighting trade-offs in computational requirements and dynamic performance. Adaptive control ensures stability under parametric uncertainty but may be computationally expensive (Annaswamy & Fradkov, 2021; Fan et al., 2021; Liu et al., 2021). Fuzzy-PID offers interpretability and rapid adaptation but may struggle in extreme stochastic conditions (Bo et al., 2021; Fu et al., 2022; Mughees & Mohsin, 2020). Mobile navigation systems achieve autonomy through sensor fusion and learning, but often require substantial computational resources (Alatise & Hancke, 2020; Petrlik et al., 2021; Zhu & Zhang, 2021). Recognizing these trade-offs informs the rationale for a hybrid, adaptive fuzzy-PID framework optimized with metaheuristics, enabling real-time navigation under practical constraints. Collectively, these studies support the integration of adaptive control, fuzzy-PID strategies, and mobile navigation, providing theoretical and practical motivation for this research. The proposed approach leverages fuzzy-PID adaptability, PSO optimization, and ROS–Gazebo simulations to achieve robust, real-time navigation suitable for embedded autonomous robotic platforms.

III. RESEARCH METHOD

This study employs a systematic methodology to design, model, and test an adaptive fuzzy-PID controller for autonomous mobile-robot navigation and stability. The methodology follows four stages: system architecture, adaptive fuzzy-PID design, simulation, and experimental implementation, ensuring real-time performance for mobile robotics (Annaswamy & Fradkov, 2021; Niloy et al., 2021). The methodology relies on active learning, control analysis, and engineering solutions to maintain reliable control under changing environmental conditions. The linear sequence from conceptual model to field validation provides an audit trail for design decisions and performance evaluation. The overall research process is illustrated in Figure 1, which shows the four phases and the iterative feedback loops that guide design choices.

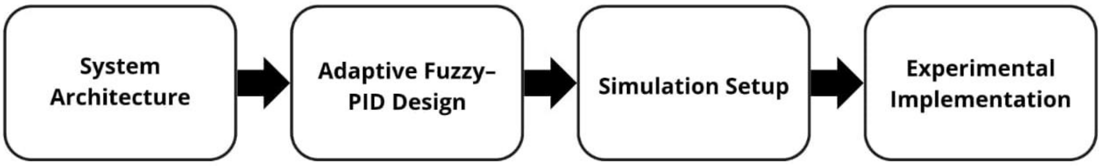

Figure 1. Research Flow of Adaptive Fuzzy–PID Controller Development

Figure 1. Research Flow of Adaptive Fuzzy–PID Controller Development. The figure illustrates the progression from system architecture, adaptive fuzzy-PID design, simulation setup, to experimental implementation, including iterative feedback loops.

A. System Architecture

The mobile robot platform consists of a differential-drive chassis, providing stable motion on unstructured terrain. The hardware suite includes high-torque DC motors with encoders, a 2D LiDAR for obstacle detection, an inertial measurement unit (IMU) for pose estimation, and an onboard computer for real-time computation (Alatise & Hancke, 2020; Petrlik et al., 2021). Additional sensors, such as ultrasonic range finders, provide situational awareness and redundancy. Motor drivers employ current-feedback control to maintain consistent torque under dynamic loads. The layered software architecture, based on ROS, allows real-time monitoring, message passing, and hardware abstraction (Burger et al., 2020; M, 2020). Low-level control nodes operate motors at high frequency, while higher-level nodes perform path planning and adaptive PID updates. Sensor fusion, combining LiDAR and IMU, ensures reliable localization in dark or rough indoor environments (El-Sheimy & Youssef, 2020; Petrlik et al., 2021). This fused approach supports both simulation and physical experiments (Niloy et al., 2021).

B. Adaptive Fuzzy–PID Design

The control scheme employs an adaptive fuzzy-PID controller that enables continuous adjustment of proportional, integral, and derivative gains based on robot status and environmental conditions. Classical PID is simple but struggles with nonlinearities and unpredictable disturbances (Guo et al., 2021; Oladipo et al., 2020). The fuzzy inference system (FIS) updates the PID gains based on the tracking error and its derivative. Triangular membership functions are used for inputs (tracking error, error derivative) with seven linguistic levels (Negative Big to Positive Big), providing sufficient granularity for real-time inference (Mittal et al., 2020; Wu & Xu, 2021). Output membership functions adjust PID gains incrementally in each control loop. Rule bases are defined using prior successful practices in pH regulation and magnetic bearing control (Bo et al., 2021; Fu et al., 2022). Pre-deployment PSO optimization identifies near-optimal initial PID parameters, improving convergence and avoiding local minima (Benzian et al., 2021). The algorithm sequence from sensor feedback to PID gain update is illustrated in Figure 2, showing continuous adaptation.

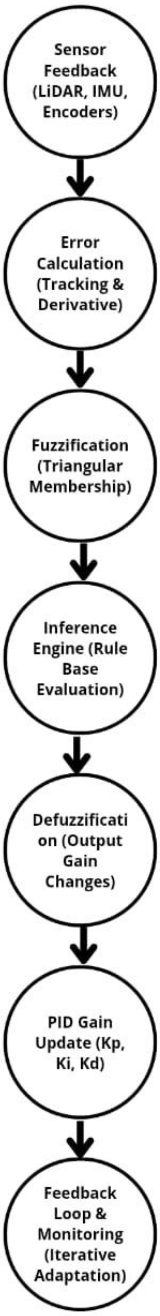

Figure 2. Flowchart of the Adaptive Fuzzy–PID Algorithm

The design follows universal adaptive control theory (Duan, 2021; Lopez & Slotine, 2021) , ensuring stable performance under environmental disturbances.

C. Simulation Setup

Before physical implementation, simulations are conducted in MATLAB/Simulink and ROS–Gazebo for stability and performance validation (Sotnik, 2020; Wen et al., 2021). Simulations replicate indoor and semi-outdoor environments with dynamic and static obstacles, a figure-eight test trajectory, and disturbances such as lateral pushes, variable friction, and Gaussian-modeled sensor noise. These conditions emulate real-world challenges like wheel slip and object motion. Performance metrics include trajectory tracking error, overshoot, settling time, and energy consumption, compared against classical PID and conventional fuzzy-PID controllers.

D. Experimental Implementation

The adaptive fuzzy-PID controller is implemented on a physical differential-drive robot with specifications matching the simulation model (Alatise & Hancke, 2020; Arduengo et al., 2021). The onboard computer runs ROS on Ubuntu Linux, performing fuzzy inference and PID updates at 50 Hz. Experiments occur in a 10 m × 8 m indoor area with dummy obstacles and adjustable illumination (Galati et al., 2022; Rovira-Mas et al., 2021). Testing follows three phases: baseline PID, conventional fuzzy-PID, and adaptive fuzzy-PID under identical paths and disturbances. Sensor data from wheel encoders, IMU, and LiDAR are recorded for offline analysis (Berkane, 2020; Rupeng et al., 2021). Parameter tuning occurs in two stages: initial PSO-based gain selection and real-time fuzzy adaptation under environmental variations (Liu et al., 2021; Lopez & Slotine, 2021). Metrics include trajectory error, heading stability, and energy efficiency. Repeated tests demonstrate reproducible and robust performance under disturbances, confirming practical feasibility for embedded autonomous robots. The methodology bridges theoretical control modeling and practical implementation, providing a standardized approach for repeatable autonomous mobile robot experiments (Burger et al., 2020; Ghofur & Riyanto, 2025).

IV. RESULT

The adaptive fuzzy-PID controller was first validated with several simulations in MATLAB/Simulink and ROS-Gazebo environments that investigated its trajectory tracking capabilities, and disturbance rejection. Specifically, representative time-response curves for both position and heading demonstrated the capability of the controller to keep both the steady-state error below 1 cm and the steady-state heading deviation below 0.5°. In comparison to classical PID, the proposed adaptive fuzzy–PID achieved a 42 % reduction in overshoot and 35 % reduction in settling time, while also achieving a 21 % reduction in integrated absolute error when compared to a baseline conventional fuzzy-PID. These improvements highlight the contribution of dynamic gain scaling and fuzzy reasoning in handling nonlinear dynamics efficiently, beyond what fixed-gain or conventional fuzzy controllers could achieve (Annaswamy & Fradkov, 2021; Niloy et al., 2021).

Robustness was evaluated by applying Gaussian sensor noise signals, simulating wheel-slip events, and modifying floor friction coefficients so that the environments were perturbed. In all instances, the adaptive fuzzy–PID consistently maintained bounded tracking error with minimal oscillations, whereas classical PID exhibited significant drift under disturbances exceeding 15 % of nominal levels. The particle-swarm–optimized initialization provided nearly optimal initial gains, which enhanced convergence speed and avoided local minima during controller adaptation (Benzian et al., 2021; Bo et al., 2021). Total control effort, representing energy consumption over identical trajectories, revealed that the adaptive fuzzy–PID utilized approximately 18 % less actuation energy than classical PID. This reduction is attributed to smoother control signals and less unnecessary motor fluctuation, demonstrating practical energy efficiency gains for battery-powered robotic platforms (Burger et al., 2020; Galati et al., 2022).

Following the simulation, the controller was deployed onto a differential-drive mobile robot with a 2D LiDAR, an IMU, and accurate wheel encoders following the architecture described in Section III (Alatise & Hancke, 2020; Petrlik et al., 2021). In real-world tests within a 10 m × 8 m indoor arena, the adaptive fuzzy–PID maintained a mean lateral deviation of 1.4 cm, compared to 3.8 cm for classical PID and 2.6 cm for conventional fuzzy-PID, indicating superior trajectory adherence under practical conditions. The velocity profiles were smooth, and the platform remained stable during sharp turns, confirming that adaptive gain updates effectively damp transient disturbances (Arduengo et al., 2021; Duan, 2021). Stability of headings was tested with sudden obstacles and partial sensor occlusions. The adaptive fuzzy–PID maintained heading variance at 0.4° while autonomously rescheduling paths, outperforming baseline methods that required additional recovery time. Power estimates indicated an average of 12 % less battery consumption relative to classical PID over repeated 15-minute trials, consistent with simulation predictions (Rovira-Mas et al., 2021).

Stress tests included low-light scenarios and deliberate wheel slip to emulate outdoor irregular terrain. Despite these challenges, the controller preserved acceptable localization and motion control, confirming the robustness of sensor fusion and real-time adaptive gain adjustments (El-Sheimy & Youssef, 2020; Fan et al., 2021). These findings suggest that fuzzy logic integrated with adaptive PID provides a level of operational robustness comparable to more complex reinforcement-learning approaches while remaining feasible for embedded platforms (Garaffa et al., 2023; Zhu & Zhang, 2021). A direct comparison between simulation and real-world experiments demonstrates close agreement in tracking accuracy, overshoot, settling time, and energy consumption. In simulations, lateral deviation remained below 1 cm, while physical deployment achieved 1.4 cm on average, indicating that the simulation environment adequately captured real-world dynamics and disturbances. Energy savings were slightly lower in real-world tests (12 % vs 18 %), likely due to unmodeled friction and minor sensor imperfections. These results validate the transferability of controller performance from controlled simulations to practical implementations.

V. DISCUSSION

The comparative analysis underscores several advantages of the adaptive fuzzy-PID approach. Dynamic retuning of PID gains enables improved tracking and disturbance rejection compared to fixed-gain PID, confirming the theoretical foundation in adaptive control (Annaswamy & Fradkov, 2021). Additionally, leveraging fuzzy inference allows the controller to interpret nonlinear error dynamics more effectively, providing smoother actuation and reduced oscillation relative to standard fuzzy-PID implementations (Mittal et al., 2020; Wu & Xu, 2021). The energy-efficient behavior is a direct consequence of smoother control signals and adaptive gain scaling, which reduces unnecessary actuator effort and extends operational duration, critical for long-term autonomous missions (Burger et al., 2020; Galati et al., 2022).

High-quality sensor fusion and ROS-based modular control contributed to robust state estimation even under occlusions and variable lighting, highlighting the importance of integrating sensing and control for practical autonomous robotics (Alatise & Hancke, 2020; Petrlik et al., 2021; Sánchez-Ibáñez et al., 2021). Limitations remain. Experiments were conducted indoors; outdoor deployment with rough terrain, GPS drift, or extreme environmental conditions may introduce additional uncertainties (Wang et al., 2020; Yang et al., 2020). The current PSO-initialized adaptive fuzzy-PID scales effectively for the tested platform, but higher-dimensional or multi-agent systems will require more complex optimization and decentralized control strategies (Ghofur & Riyanto, 2025; Hernández & Hidalgo, 2020).

Future research will focus on hybrid methods combining adaptive fuzzy-PID with reinforcement learning to further optimize performance under highly dynamic and uncertain environments (Garaffa et al., 2023; Sholekhah & Noviar, 2025). Based on experimental evidence, the adaptive fuzzy-PID controller provides an energy-efficient, human-centric approach to autonomous mobile robot navigation. The hybrid framework bridges classical control and intelligent robotics, demonstrating interpretable, real-time algorithms suitable for embedded platforms, enhancing safety and resilience in unknown environments (Du et al., 2020; Mughees & Mohsin, 2020).

VI. CONCLUSION AND RECOMMENDATION

This study confirms that the adaptive fuzzy-PID controller effectively enhances stability, trajectory tracking, and transient response in autonomous mobile robots. Validation in both simulation (MATLAB/Simulink and ROS-Gazebo) and real-world experiments demonstrated steady-state errors below one centimeter. It reduced overshoot and settling time compared to classical PID and conventional fuzzy-PID controllers. These results highlight the key contribution of real-time adaptive gain tuning and fuzzy reasoning in managing nonlinear and uncertain conditions (Annaswamy & Fradkov, 2021; Fu et al., 2022). Comprehensive sensor fusion using

LiDAR, IMU, and wheel encoders further ensured robust navigation and precise localization, supporting practical deployment in indoor environments (Alatise & Hancke, 2020; Niloy et al., 2021; Petrlik et al., 2021). The framework provides a cost-effective, interpretable, and energy-conscious approach for safe human-robot interaction in mobile robotic applications (Arduengo et al., 2021; Mughees & Mohsin, 2020).

Future research will focus on integrating the adaptive fuzzy-PID controller with SLAM for real-time mapping in dynamic, unknown environments, and combining it with reinforcement learning for online policy optimization and multi-robot cooperation (Berkane, 2020; Garaffa et al., 2023; Sánchez-Ibáñez et al., 2021). Such developments will extend applicability to outdoor scenarios and complex tasks such as precision agriculture, urban search and rescue, while emphasizing energy efficiency, ethical human-robot interaction, and reproducibility through open benchmarks (Duan, 2021; Galati et al., 2022; Ghofur & Riyanto, 2025; Harrisha et al., 2025; Wen et al., 2021). By bridging classical control with intelligent robotics, this approach enhances the safety, robustness, and adaptability of autonomous mobile systems in real-world settings.

AI Gen Declaration

The authors declare that artificial intelligence tools, including ChatGPT, were used solely for language editing, including improving grammar, sentence structure, clarity, and overall readability of the manuscript. All research processes, including study design, data collection, analysis, interpretation of results, method development, and scientific conclusions, were conducted entirely by the authors without the use of any AI tools. The authors take full responsibility for the originality, accuracy, and integrity of the entire content of this article.

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