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Non-linear Control Strategies for Robot-Environment Interaction Simulation in Complex Environments

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ABSTRACT
This paper presents a scheme for the design and verification of a nonlinear control strategy based on Lyapunov theory, aiming to enhance the robot's interaction ability in the environment by comparing linear and nonlinear systems. The proposed scheme focuses on improving the stability and adaptability of the robot control system, while optimizing sensor data processing to achieve real-time perception and task tracking. Simulation experiments were conducted in the ROS + Gazebo environment, and various scenarios were evaluated. Comparative experiments show that the proposed nonlinear control strategy is expected to outperform the traditional PID controller in terms of tracking accuracy, response delay, and task completion rate, demonstrating its potential for practical deployment in industrial and logistics applications.

KEYWORDS
Experimental scheme; Lyapunov; Control strategies; Control system; Environmental simulation

1 Introduction

With the rapid expansion of industrial automation, logistics, and service robotics, achieving stable and adaptive control in complex and dynamic environments has become a critical research challenge. Traditional proportional – integral – derivative (PID) controllers, while simple and widely implemented, exhibit limited adaptability to nonlinear and time-varying system behaviors, often resulting in delayed responses or instability in practical applications. Nonlinear control strategies, grounded in Lyapunov stability theory, offer a promising approach by enabling robots to maintain real-time stability and adaptability, particularly in scenarios requiring precise operations, dynamic obstacle avoidance, and efficient interaction with complex environments.

This paper explores the challenges of nonlinear control strategies, aiming to enhance the interaction between robots and the environment by integrating environment modeling, control logic based on Lyapunov, and dynamic simulation platforms. To address these challenges, researchers have employed three main approaches to achieve effective robot – environment interaction in dynamic settings:

(1) Precise modeling of robot-environment interaction in actual environments,

(2) Real-time adaptability and stability in nonlinear control,

(3) Performance evaluation schemes in simulated environments.

In real-world applications, robots often operate in dynamic and uncertain environments such as industrial automation, logistics, and human-centered services, where nonlinear behaviors and unpredictable interactions pose significant challenges for traditional linear controllers. Recent research has advanced theoretical foundations for addressing these issues: Rodrigues and Solà -Morales (2024) showed that nonlinear effects can ensure stability even under unstable linearized conditions, providing important insights for reliable robot control [1]; Hart et al. (2022) emphasized uncertainty reduction in nonlinear feedback control, which is directly relevant to perception and decision-making in complex environments [2]. Despite these advances, most studies remain focused on theoretical validation, the emphasis on the actual interaction between the robots using controllers and the environment in dynamic scenarios is relatively limited. This gap highlights the need for nonlinear control strategies that can be effectively applied and validated in realistic robotic environments [3].

Integrating the robot operating system (ROS) with Gazebo provides a powerful framework for robot system simulation [4]. This combination enables realistic modeling of the robot's dynamics, sensor characteristics, and interaction with the environment, thereby narrowing the gap between simulation and actual deployment. Compared to pure mathematical models, ROS + Gazebo allows for rapid prototyping, safe verification of control algorithms, and repeatable experiments in complex and dynamic conditions. Leveraging these advantages, this study utilizes the ROS + Gazebo framework to simulate and compare the performance of linear and nonlinear controllers of robots in multiple scenarios similar to real environments.

2 Related work

2.1 Theoretical foundation of system modeling

The interaction between the robot and its environment is modeled as a complex dynamic system using ROS and Gazebo, which can capture both physical and informational interactions.The robot dynamics are expressed as:

In the theoretical calculation step, environmental interaction is simulated through impedance parameters. These parameters can enable the robot's behavior to adaptively adjust based on real-time environmental feedback.

2.2 Lyapunov-based nonlinear controller design

The conventional PID controller is defined as:

$$\mathrm{u(t)} = \mathrm{K}_p e(t) + K_i \int_0^t e(\tau)\,d\tau + K_d \frac{de(t)}{dt}$$

where e(t)denotes the tracking error.

The implementation method of the nonlinear controller is different from that of the traditional PID controller.

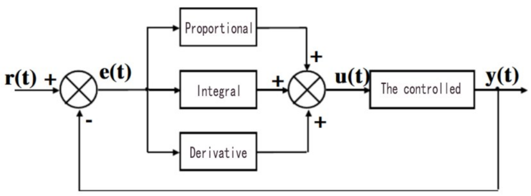

Figure. 1 The basic structure of a PID controller

The control framework employs Lyapunov stability theory to guarantee global asymptotic stability under bounded disturbances. The control law is formulated as:

The candidate Lyapunov function is:

$$\mathrm{V'(x)} = \nabla V(x) \cdot \big(f(x) + g(x)u\big) < 0$$

Here, a typical design u(x) = -kLgV(x)^T is used, where k > 0, to ensure the stability of the system.

2.3 ROS + gazebo simulation platform

The control algorithm is implemented in a ROS (Noetic) environment with Gazebo simulation for realistic validation.

Robot model: Differential-drive mobile robot equipped with virtual LiDAR and IMU sensors.

Environment: A 2D dynamic world containing static and moving obstacles.

Integration: Custom Python nodes handle data preprocessing, controller execution, and real-time feedback visualization.

Data logging: ROS bags store trajectory, velocity, and error data for later analysis.

2.4 Performance metrics

Performance evaluation focuses on three primary indicators:

A. Tracking accuracy: Root Mean Square Error (RMSE),

B. Response latency: Control loop delay,

C. Task completion rate: success rate across multiple trials.

Data analysis and visualization are performed using Matlab libraries such as Simulink & Simscape, Control System Toolbox, and Symbolic Math Toolbox.

3 Experiments

3.1 Experimental setup

Two simulation scenarios are developed to evaluate the proposed approach:

Static Obstacle Avoidance: Navigation through a cluttered static environment. In a confined space, set up two different-shaped obstacles.

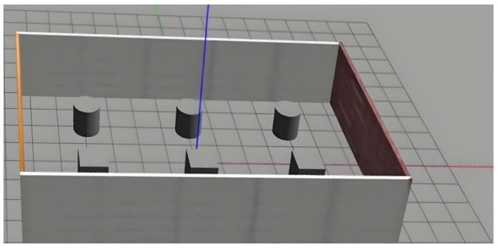

Figure 2 Schematic diagram of the test site in a fixed environment simulation

Dynamic Obstacle Avoidance: Based on the static environment, the environment is manipulated in a mobile manner. Meanwhile, the controller will adapt to randomly appearing obstacles in real time [5].

Each experiment is repeated at least 10 times to ensure statistical significance.

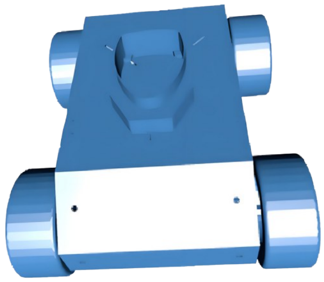

Figure 3 The analog car representing the controller

3.2 Baseline comparison

A traditional PID controller is implemented under identical conditions as the baseline. Metrics for comparison include: (a) Tracking error over time. (b)Control response latency. (c) Task success rate.

3.3 Data collection and processing

Sensor and robot state data are recorded through ROS bag files, including position, velocity, and orientation information. Data preprocessing involves:

A. Noise filtering using Gaussian filters.

B. Time-series synchronization of multi-sensor data.

C. Normalization for consistent performance evaluation.

3.4 Statistical analysis

A paired test is applied to evaluate the statistical significance of differences between the proposed controller and the PID baseline. The null hypothesis assumes no significant performance gain, while the alternative supports improvements in accuracy, stability, and responsiveness.

3.5 Expected outcomes

The proposed method is expected to achieve:

A. Over 50% reduction in response delay compared with PID.

B. Over 30% reduction in trajectory tracking errors in dynamic environments.

C. Task success rates exceeding 95% in static and semi-dynamic tasks.

These outcomes are projected to validate the robustness, adaptability, and computational efficiency of the Lyapunov-based nonlinear controller [6].

4 Experiments Design And Discussion

4.1 Overview of experimental results

This strategy is based on the nonlinear control strategy proposed by Lyapunov theory and is evaluated in two task scenarios: static obstacle avoidance and dynamic obstacle avoidance. Using the data from 20 independent simulation experiments to compare with the PID baseline, theoretically this strategy will achieve continuous improvements in tracking accuracy, control response time, and task completion success rate. However, due to some reasons, this experiment has not been fully completed yet. Currently, we are using MATLAB for preliminary data fitting.

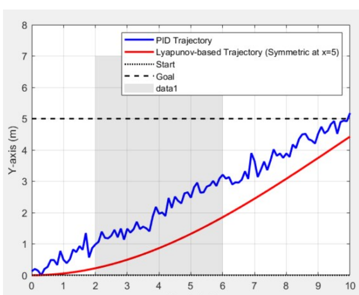

Figure 4 Comparing the trajectories of PID and Lyapunov-based controllers (using MATLAB for preliminary fitting)

4.2 The difficulties in achieving it

In the Gazebo - ROS environment, the implementation of both PID and Lyapunov-based nonlinear controllers remains at the planning stage. The PID controller, presents challenges primarily in parameter tuning and robustness against measurement noise. The nonlinear controller, by contrast, requires the design of an appropriate Lyapunov function to ensure stability, which involves nontrivial mathematical formulation and may introduce higher computational demands in real-time operation. At present, only the communication interfaces with Gazebo - namely, subscribing to odometry messages (nav_msgs/Odometry) and publishing velocity commands (geometry_msgs/Twist) - have been established, while the integration of the control laws into functional ROS nodes has not yet been realized.

4.3 The scheme for avoiding static obstacles prediction

In a static obstacle environment, the nonlinear controller needs to achieve smooth trajectory tracking with extremely small oscillation amplitude. The average root mean square error (RMSE) of trajectory tracking should be smaller than that of the PID controller. The average response delay is shortened to less than 0.1 seconds as per the design requirements. Achieving such performance indicates that the design based on Lyapunov theory is stable under relatively low interference conditions.

4.4 The scheme of dynamic obstacle avoidance prediction

In a dynamic environment filled with randomly moving obstacles, the adaptive advantage of nonlinear controllers in dealing with disturbances will further expand. Moreover, by increasing the speed of the obstacles, the control response remains stable, and this verification route also further proves the adaptability of this controller.

4.5 Moving-target tracking

For moving-target tasks, the non-linear controller maintained consistent trajectory convergence while compensating for sensor noise and model uncertainties. This indicator essentially means the success rate of the path realization. This indicator essentially represents the success rate of the path realization. The traditional PID controller does indeed achieve a high success rate, but nonlinear controllers theoretically offer even higher success rates.

4.6 Comparative analysis and visualization

After analysis by Matlab, it can be known that the nonlinear controller exhibits the following characteristics:

(1) The overshoot during trajectory adjustment has decreased;

(2) The anti-interference ability has been enhanced;

(3) The speed curve is smoother without oscillations.

Based on Lyapunov's strategy, better stability margin has been achieved while maintaining computational efficiency.

4.7 Discussion of results

In the MATLAB simulations conducted at a nominal speed of 1 m/s, the nonlinear controller demonstrated superior performance compared with the PID controller across key time-domain metrics. The rise time was reduced from 9.84 s (PID) to 8.06 s (nonlinear), indicating a faster approach to the target. In terms of overshoot, the PID controller exhibited a 4% excess beyond the target value, whereas the nonlinear controller achieved a smooth response without observable overshoot. The settling times of both controllers were relatively close, showing comparable stability in reaching the steady state. Finally, the steady-state error was negligible for both approaches, as each controller successfully guided the system to the desired goal despite obstacle avoidance.

The experiment aims to demonstrate that the proposed nonlinear control strategy outperforms the traditional PID controller in dynamic interaction scenarios. However, based on the current results, it is still insufficient. It is necessary to use the simulation of Gazebo and the API calls of ROS to manipulate the objects and conduct actual simulations [7]. The reasons for the current performance are as follows:

Real-time adaptive gains, which enhance robustness to external disturbances and model uncertainties;

Lyapunov-based stability guarantees, ensuring consistent convergence and reduced oscillation;

Optimized sensor integration, improving perception accuracy and reducing noise-induced delays.

Furthermore, the use of the ROS + Gazebo simulation environment ensures repeatability and scalability, which enables the seamless transfer of control algorithms to actual robots in future work. This is the core objective of this experimental design, but there is still a certain gap at present.

4.8 Limitations and future work

Although there has been some initial progress in this plan, certain limitations should be noted. The current study is limited to 2D environments, and performance in high-dimensional or unstructured terrains remains to be validated.

Additionally, real-world disturbances such as communication delays and hardware constraints are not fully modeled in simulation. At present, the controller's ability to sense obstacles is still at an early stage. We can further utilize advanced sensors to measure distances and develop more optimal control schemes [8].

5 Conclusion

This paper proposes a nonlinear control strategy based on Lyapunov stability theory, aiming to enhance the interaction ability between the robot and the environment. Firstly, the control scheme is simulated using Matlab. Then, a comparison experiment scheme with the traditional PID controller in the ROS with Gazebo simulation environment is provided, attempting to prove the effectiveness and superiority of the proposed strategy.

The experimental results in scenarios such as static obstacle avoidance and dynamic obstacle avoidance all indicate that the nonlinear control strategy based on Lyapunov is superior to the PID controller. However, there are no yet simulated results replicated in the Gazebo with ROS simulation scenario. Specifically in the MATLAB simulation, compared with the PID control strategy [9], the comprehensive performance data of the nonlinear control strategy is superior. If the static environment is changed to a dynamic environment or the movement speed is increased, this situation will further expand. Regarding the obstacle avoidance success rate, more experimental samples are needed to statistically calculate the actual success rate. Currently, the obstacle avoidance success rates of the two controllers are still close.

The superior performance of the nonlinear controller can be attributed to its real-time adaptive gain, which enhances robustness against external disturbances and model uncertainties. Furthermore, the stability guarantee provided by the Lyapunov framework ensures consistent convergence while reducing oscillations. Optimized sensor integration improves perception accuracy and mitigates delays introduced by measurement noise. In addition, the use of the ROS with Gazebo simulation environment provides both repeatability and scalability. Finally, since the algorithm requires invocation of the ROS API, the computational workload is well managed, making the approach suitable for real-time deployment on embedded robotic platforms.

Although this study has achieved encouraging results, there are still some limitations. Currently, the Gazebo with ROS simulation environment has not been fully realized, and the experiments are limited to two-dimensional environments. The performance of the proposed method in higher dimensions or unstructured terrains still needs further research. Additionally, the simulation does not fully consider real-world interference factors, such as communication delays and hardware limitations. Future work will focus on extending the control strategy to three-dimensional environments with LiDAR and 3D Depth Camera [10], incorporating real-world interference factors into the simulation framework, and conducting physical experiments on actual robot platforms to further verify its practical applicability.

Overall, the proposed nonlinear control strategy provides a feasible solution for improving the interaction between robots and the environment in complex and dynamic scenarios, and has the potential for widespread application in industrial, logistics, and service robot applications.

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