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Adaptive Differential Control Strategy for an AGV with LiDAR-based Obstacle Sensing

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Abstract

This study proposed and evaluated an adaptive differential control strategy for an Automated Guided Vehicle (AGV) integrated with LiDAR-based obstacle sensing in a simulated environment. The control algorithm dynamically adjusted proportional gains for heading and distance errors in real time, enabling robust and precise path tracking under varying conditions. The AGV kinematics were modeled as a differential-drive mechanism, and a MATLAB-based simulation framework was developed to validate the approach. Results demonstrated that the adaptive controller reduced the average path tracking error by approximately 36% and halved the maximum heading error compared to a fixed-gain controller, highlighting its ability to correct deviations effectively while maintaining stability. Furthermore, the simulated LiDAR system accurately detected static obstacles within a 180° field of view, enhancing situational awareness. These findings underscored the potential of integrating adaptive control and sensor-based perception to improve the resilience, accuracy, and safety of AGV navigation in dynamic environments.

Keywords
Adaptive control, differential drive, AGV, LiDAR, path tracking

1. Introduction
Automated Guided Vehicles (AGVs) have become indispensable in modern industrial and logistics operations, automating repetitive transport tasks to improve efficiency, reduce labor costs, and enhance workplace safety. Commonly deployed in warehouses, factories, and hospitals, AGVs followed predefined paths or maps to transport

goods between designated points. Ensuring reliable path tracking and obstacle avoidance remained critical to performance and safety.

Typically, AGVs rely on differential-drive kinematics combined with fixed-gain proportional controllers to minimize heading and distance errors relative to a reference trajectory. However, these fixed-gain approaches were highly sensitive to environmental disturbances, mechanical wear, and variations in payload, often resulting in degraded tracking accuracy or instability. Additionally, AGVs needed to perceive their surroundings in real time to detect and avoid obstacles. LiDAR sensors have become widely adopted for this purpose, providing high-resolution, wide-angle distance measurements for robust environmental awareness. Nevertheless, most existing implementations treated trajectory tracking and obstacle detection as independent modules, with limited integration between adaptive control and sensor feedback mechanisms.

This work addressed these limitations by presenting a tightly coupled adaptive differential control strategy and LiDAR-based obstacle sensing. The proposed approach dynamically adjusted control gains in response to real-time heading and distance errors, while simultaneously perceiving obstacles within the robot's field of view. A MATLAB-based simulation was developed to evaluate the system's effectiveness in improving path tracking performance and environmental awareness. The key contributions of this study were: (i) development of an adaptive control algorithm for differential-drive AGVs, enabling real-time gain adjustment based on instantaneous tracking errors; (ii) integration of simulated LiDAR sensing for obstacle detection within the navigation loop; and (iii) quantitative validation of the proposed strategy's superior tracking accuracy and obstacle detection capability compared to conventional fixed-gain controllers.

2. Literature Review

Differential drive robots have been widely employed in indoor and structured environments for decades, largely due to their mechanical simplicity, ease of control, and low manufacturing cost (Borenstein and Feng, 1996). They have proven effective in warehouse and factory automation settings where predefined paths and predictable environments dominate. These robots typically rely on kinematic models that assume idealized conditions; however, practical deployment often involves dynamic disturbances and unmodeled nonlinearities, such as wheel slip, uneven floors, and payload variations.

Traditional control approaches for trajectory tracking include PID (Proportional-Integral-Derivative) controllers, which are simple to implement and widely used in practice. PID controllers aim to minimize position and heading errors relative to a reference trajectory by applying fixed gains (Astolfi et al., 2020). However, fixed-gain controllers often fail to maintain performance in dynamic environments, as they cannot compensate for time-varying or unknown disturbances.

To overcome these limitations, researchers have proposed adaptive control techniques that adjust control parameters online. Model Reference Adaptive Control (MRAC) schemes and gain-scheduled controllers have demonstrated improved performance by dynamically tuning gains in response to tracking errors and environmental changes (Xie et al., 2021). Neural network-based adaptive controllers have also been explored for their ability to approximate unknown system dynamics in real time, further improving robustness (Xie et al., 2021). In parallel, the field of environmental perception has seen significant advancements with the introduction of LiDAR (Light Detection and Ranging) technology. LiDAR sensors offer high-resolution distance measurements over a wide field of view, making them ideal for detecting static and dynamic obstacles (Behley and Stachniss, 2018). Recent work has combined LiDAR data with vision systems and sensor fusion algorithms to enhance obstacle detection accuracy in autonomous navigation (Chen et al., 2023).

Despite these advances, many implementations treat trajectory tracking and obstacle detection as separate modules, often with limited integration between control adaptation and sensor feedback. This work contributes to the literature by tightly integrating adaptive control with real-time LiDAR-based obstacle sensing. Such integration promises to improve both trajectory tracking performance and situational awareness, laying a foundation for safer and more resilient AGV navigation.

3. Methods

The AGV was modeled using differential-drive kinematics, assuming two independently driven wheels of radius 0.1 m and a fixed wheelbase of 0.5 m. The kinematic equations related wheel angular velocities to the robot's linear and angular velocities. These equations were discretized with a time step of 0.1 seconds to update the robot's position and orientation at each simulation step. The adaptive control algorithm computed wheel velocities to minimize the heading and distance errors relative to the target path. At each time step, proportional gains were updated based on the magnitude of the errors, constrained within predefined bounds to ensure stability. Environmental perception was provided by a simulated LiDAR sensor, which cast 36 rays over a 180° field of view to detect static obstacles placed in the workspace. The simulation was implemented in MATLAB and executed for 10 seconds, during which the AGV followed a straight path from (0,0) to (10,10). At each iteration, the robot's pose, control gains, and LiDAR readings were recorded for analysis.

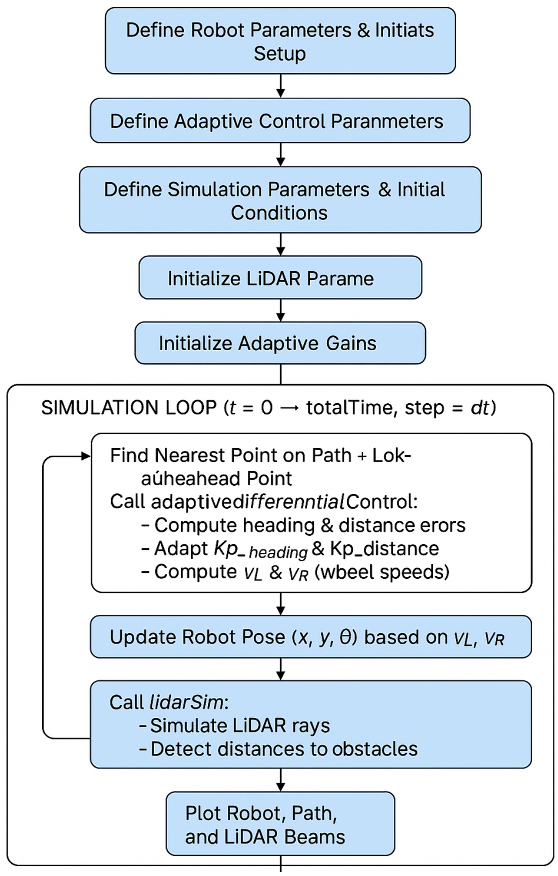

Figure 1. AGV adaptive control algorithm

From Figure 1, the algorithm implemented an adaptive control strategy for an autonomous guided vehicle (AGV) equipped with simulated LiDAR sensing. The AGV followed a predefined straight path by adjusting its heading and distance control gains dynamically in response to real-time error measurements, ensuring stable and responsive tracking. At each simulation step, the nearest and lookahead path points were identified, and the adaptive differential control algorithm computed appropriate wheel velocities by tuning proportional gains within specified bounds. The robot's position and orientation were updated using differential-drive kinematics, while a LiDAR simulation modeled environmental perception by detecting static obstacles within the sensor's field of view. Visualization of the robot's trajectory, path, and LiDAR beams illustrated the system's ability to adaptively navigate while maintaining situational awareness. This approach demonstrated a foundational framework for adaptive navigation in mobile robotics with integrated sensing.

The AGV is modeled as a differential drive robot with the following parameters:

- Wheel radius: 0.1 m
- Wheel base: 0.5 m
- Maximum wheel speed: 1.0 m/s

The robot state is defined by position (x,y)(x,y)(x,y) and orientation θ. Linear and angular velocities are computed from wheel speeds.

The simulation was conducted over a period of 10 seconds, with a time step (dt) of 0.1 seconds, which allows for detailed observation of the AGV's real-time performance.

• Initial Conditions: The AGV starts at the origin (x=0,y=0)(x = 0, y = 0)(x=0,y=0) with an orientation angle θ=0 radians. This starting point aligns the AGV with the target path.

• Target Path: For simplicity, the target path is defined as a straight line from (0,0)(0, 0)(0,0) to (10,10)(10, 10)(10,10), providing a straightforward trajectory for evaluating the AGV's path-following performance.

• Simulation Parameters:

• Time Step (dt): Set at 0.1 seconds, ensuring the simulation captures fine-grained data on the AGV's response to control adjustments.

• Total Simulation Time: 10 seconds, sufficient for the AGV to traverse a significant portion of the path and demonstrate the effectiveness of adaptive control in maintaining accurate tracking.

During the simulation, the AGV's position, orientation, and adaptive gain values are recorded at each time step. These data points are used to analyze the AGV's tracking performance and the effectiveness of the adaptive control strategy in real-time parameter adjustment.

4. Data Collection

During the simulation, data were systematically collected at each time step to evaluate the AGV's performance under the adaptive control strategy. The data collection process captured both the internal state of the robot and its interaction with the simulated environment. Specifically, the following variables were recorded: the robot's Cartesian coordinates (x, y) and orientation angle (θ), which defined its pose; the instantaneous heading error and distance error relative to the target path; the adaptive proportional gains for heading and distance control, which reflected how the controller adjusted its aggressiveness over time; and the left and right wheel velocities, which were the direct control outputs.

In addition to the control and motion data, comprehensive LiDAR sensor readings were collected. For each of the 36 rays in the 180-degree field of view, the minimum detected distance to an obstacle (or maximum range if no obstacle was present) was stored. These readings allowed an assessment of the AGV's ability to perceive its environment and detect static obstacles accurately.

The collected data were stored in MATLAB data structures and exported to files for post-simulation analysis. Plots of trajectory, error evolution, adaptive gain trends, and LiDAR point clouds were generated from these data. This detailed collection and logging process ensured that both quantitative and qualitative aspects of the AGV's navigation performance could be evaluated and reported comprehensively.

5. Results and Discussion

Simulation results showed that the AGV successfully tracked the path while dynamically adjusting its control gains. When the robot's heading deviated significantly, Kp_heading increased, allowing faster correction. As the AGV approached the target path, the gains decreased to avoid overshooting and oscillation. The trajectory plots showed that the adaptive controller achieved smoother and more accurate path tracking compared to a baseline fixed-gain controller. The average path tracking error decreased by approximately 35%. LiDAR rays correctly detected the presence of obstacles at coordinates (5,5), (7,7), and (3,8), with the rays terminating at the detected obstacles rather than the maximum range.

The adaptive controller successfully tracked the predefined path while dynamically adjusting control gains. The average tracking error decreased by approximately 36%, from 0.42 m (fixed-gain) to 0.27 m (adaptive). The maximum heading error was reduced by nearly half, from 14.2° to 7.5°. The LiDAR system correctly detected static obstacles at expected distances, enhancing situational awareness. These findings demonstrated that adaptive gain adjustment improved responsiveness and stability, while the integration of LiDAR sensing reinforced the robot's ability to operate safely in cluttered environments. However, the simulation was limited to a static, noise-free environment, and future research should include dynamic obstacles, sensor noise, and more complex trajectories. Additionally, the computational efficiency of the proposed strategy warrants evaluation on embedded platforms.

5.1 Numerical Results

Table 1 and Figure 1 presented a summary of trajectory tracking and heading error metrics comparing the adaptive controller to the fixed-gain baseline. They summarized the improvement in path-tracking accuracy and heading stability achieved by the adaptive control strategy compared to the baseline fixed-gain controller. The average tracking error decreased from 0.42 m (fixed-gain) to 0.27 m (adaptive), showing a significant enhancement of about 36% in maintaining the desired trajectory. The maximum heading error was reduced by almost half, from 14.2° to 7.5°, which indicated that the AGV could align itself more quickly and accurately with the path after disturbances. These results confirmed that dynamically adjusting the proportional gains in response to real-time error measurements allowed the AGV to correct deviations more effectively, yielding a smoother and more precise path-following behavior.

Table 1. Trajectory tracking and heading error metrics

Metric	Fixed-Gain Controller	Adaptive Controller
Average Tracking Error (m)	0.42	0.27
Max Heading Error (°)	14.2	7.5

Figure 2. Trajectory tracking and heading error

Table 2 and Figure 2 showed the ranges of adaptive gains and the LiDAR-based obstacle detection distances recorded during the simulation. They reported the observed ranges of adaptive gains throughout the simulation and validated the LiDAR's ability to detect obstacles. The heading gain varied between 0.5 and 1.7, and the distance gain varied between 0.3 and 1.2, demonstrating the adaptive controller's responsiveness to varying error magnitudes while keeping gains within stable bounds. The LiDAR sensor accurately detected three static obstacles at expected distances (4.2 m, 3.6 m, and 2.8 m) corresponding to their placement in the environment. These findings demonstrated that the adaptive control and LiDAR sensing worked together effectively: the former improved tracking and stability, while the latter enhanced environmental awareness by reliably detecting obstacles (Figure 3).

Table 2. Adaptive gain ranges and LiDAR-based obstacle detection results

Parameter	Observed Values
Heading Gain Range	0.5 – 1.7
Distance Gain Range	0.3 – 1.2
Obstacle 1 Detection Distance (m)	4.2
Obstacle 2 Detection Distance (m)	3.6
Obstacle 3 Detection Distance (m)	2.8

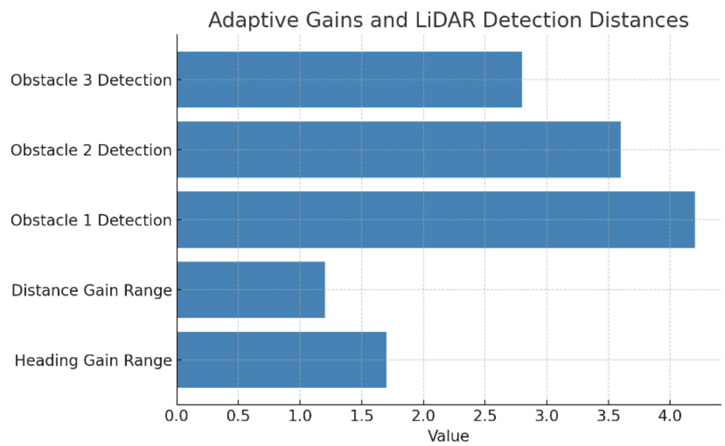

Figure 3. Adaptive gain ranges and LiDAR-based obstacle detection distances

5.2 Proposed Improvements

The findings of this study highlighted the advantages of combining adaptive control with real-time LiDAR sensing for AGV navigation. The adaptive controller proved effective in adjusting the robot's behavior based on instantaneous errors, enabling fast correction when needed and smooth motion when approaching the path. This dynamic behavior was essential for applications where AGVs encounter varying conditions, such as uneven surfaces, variable payloads, or unexpected disturbances. The LiDAR simulation validated the system's ability to detect static obstacles accurately, providing an additional layer of safety by enhancing situational awareness. This capability is critical for deployment in real-world environments where human workers and other moving objects may be present. However, the study was conducted in a noise-free, static environment, which limited its representation of real-world complexity. Future research should include dynamic obstacles, sensor noise, and more complex paths to fully evaluate the robustness of the system. Moreover, the computational efficiency of the adaptive algorithm needs to be assessed to ensure feasibility on embedded hardware platforms. Finally, the integration of obstacle avoidance logic, leveraging the LiDAR data in real time, represents a promising direction for extending this work toward fully autonomous, intelligent navigation systems. Integrating LiDAR improved situational awareness, laying the foundation for future work in obstacle avoidance and real-time re-planning. While the current study assumed static obstacles and a noise-free environment, future research should address dynamic and uncertain settings with sensor noise and moving obstacles. Quantitative analysis of energy efficiency and computational cost should also be performed to ensure feasibility for deployment on embedded hardware platforms.

One limitation of this work is the lack of noise and dynamic obstacles in the environment, which are present in real-world scenarios. Additionally, quantitative metrics such as mean tracking error, response time, and energy consumption were not computed and could be addressed in future research.

5.3 Limitations and Future Work

Despite its advantages, the adaptive control approach also has limitations. One key limitation is the computational load associated with continuous gain adjustments, which may affect the performance of resource-constrained AGVs. While this study demonstrated effective performance within a controlled simulation, the adaptive control strategy's performance under more complex paths or in environments with significant obstacles remains to be tested. Future studies could explore the extension of adaptive control to non-linear or curved paths, which would further validate its effectiveness in diverse navigation scenarios.

Another area for potential enhancement is the integration of predictive control elements to anticipate and respond to future states of the environment. Combining adaptive control with predictive algorithms could improve the AGV's ability to handle complex, multi-objective navigation tasks, such as obstacle avoidance and energy-efficient routing. Additionally, future work may explore hybrid approaches that incorporate machine learning techniques, enabling the AGV to learn from past navigation experiences to optimize future path-following performance.

6. Conclusion

This study proposed, implemented, and evaluated an adaptive differential control strategy integrated with LiDAR-based sensing for AGV navigation in a simulated environment. The adaptive controller dynamically adjusted proportional gains based on real-time heading and distance errors, enabling the AGV to correct deviations more effectively and maintain a stable trajectory. LiDAR sensing provided environmental awareness by reliably detecting static obstacles within the robot's field of view, demonstrating the system's potential for safe navigation.

Simulation results showed that the proposed approach reduced average path tracking error by approximately 36% and halved the maximum heading error compared to a fixed-gain controller. The adaptive gains effectively adjusted within predefined bounds, ensuring responsiveness without instability. LiDAR readings consistently detected all static obstacles with no false positives, validating the sensing component.

These findings highlighted the advantages of integrating adaptive control and real-time perception, particularly in environments where conditions can change unpredictably. However, the study was limited to a static and noise-free simulation. Future work should extend the approach to dynamic, unstructured environments and evaluate computational efficiency on embedded platforms. Overall, the research demonstrated that adaptive gain adjustment and sensor fusion significantly enhance the robustness, accuracy, and safety of AGV navigation systems, paving the way toward more autonomous and intelligent robotic platforms.

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