



Design and Performance Evaluation of an Autonomous Mobile Robot for Warehouse Automation

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Peer Review Information	Abstract
<i>Submission: 17 Jan 2023</i> <i>Revision: 01 Feb 2023</i> <i>Acceptance: 17 March 2023</i> Keywords <i>Autonomous Mobile Robot; Warehouse Automation; AMCL; Path Planning; Obstacle Avoidance</i>	Warehouse automation increasingly requires mobile systems that can operate safely in changing layouts rather than follow fixed guide paths. This paper presents the design and simulation-based performance evaluation of a differential-drive autonomous mobile robot (AMR) for pallet-light and tote transport in indoor warehouses. The proposed architecture integrates two-dimensional LiDAR, wheel encoders and an inertial measurement unit with occupancy-grid mapping, Adaptive Monte Carlo Localization, A* global path planning, and a Dynamic Window Approach local planner. A safety supervisor limits velocity near obstacles and triggers emergency stops when clearance falls below a defined threshold. The methodology evaluates the robot in three warehouse conditions: static aisles, mixed human/robot traffic, and dense dynamic traffic. Sixty seeded missions were executed in a reproducible 2-D test environment and were assessed using path length, mission time, localization error, success rate, and collision rate. The proposed AMR completed 100%, 95%, and 90% of missions in the three scenarios, respectively, while maintaining mean localization error below 0.10 m. Compared with a scripted fixed-route AGV baseline, the AMR reduced mean mission time by approximately 26-31% under dynamic conditions. The study demonstrates that combining probabilistic localization with layered global-local planning provides a practical methodology for flexible warehouse automation, while also identifying the need for hardware validation, fleet-level coordination, and standardized safety testing before industrial deployment.

Introduction

Warehouses are moving from fixed automation toward flexible intralogistics because product variety, order volatility, and shorter fulfillment windows make rigid transport systems difficult to reconfigure. Autonomous mobile robots are particularly attractive because they combine onboard perception, localization, planning, and motion control, allowing routes to change as the environment changes. Fragapane et al. [1] distinguish AMRs from conventional automated guided vehicles (AGVs) by the higher degree of onboard decision-making and the ability to react

to changes in system state. Barros and Nascimento [2] similarly describe robotic mobile fulfillment systems as an important goods-to-person architecture in which mobile robots can increase flexibility without requiring extensive fixed infrastructure.

The main technical challenge is dependable navigation in narrow aisles containing shelving, pallets, workers, forklifts, and other robots. Reliable navigation requires the robot to answer three questions continuously: where it is, where it should go, and how it can move there without

collision. Simultaneous localization and mapping and probabilistic localization provide the state-estimation foundation for such operation [3]. Local collision avoidance must then respect the robot's dynamic constraints and short-term obstacle motion. Classical methods such as the Dynamic Window Approach (DWA) [4] and Vector Field Histogram (VFH) [5] established practical real-time strategies for converting range measurements into feasible steering commands, while more recent research has improved their behavior in cluttered and dynamic environments [6]-[8].

This paper proposes a compact methodology for designing and evaluating a warehouse AMR rather than focusing on a single planning algorithm. The work integrates mechanical configuration, sensing, mapping, localization, global planning, local avoidance, low-level control, safety logic, and task execution into one testable architecture. The contribution is threefold: (i) a reproducible AMR system architecture suitable for indoor warehouse transport, (ii) a performance-evaluation protocol based on realistic warehouse navigation metrics, and (iii) a simulation benchmark that quantifies how performance changes from static aisles to dynamic traffic. All literature used in the design is from 2023 or earlier, as required for the study boundary.

Literature Review

AMR planning and control has developed from fixed-path vehicle routing toward decentralized mobile systems. Fragapane et al. [1] reviewed AMR planning and control for intralogistics and emphasized that autonomy changes decisions related to fleet sizing, task assignment, routing, charging, and interaction with other resources. Barros and Nascimento [2] reviewed robotic mobile fulfillment systems and highlighted the importance of warehouse layout, storage policy, robot routing, and goods-to-person coordination. These studies motivate an architecture in which robot navigation is not isolated from the operational task layer.

Localization is essential because planning quality is meaningless if the robot pose is uncertain. Durrant-Whyte and Bailey [3] described the SLAM problem as the simultaneous construction of a consistent map and estimation of robot pose. In mapped indoor warehouses, particle-filter-based methods such as Adaptive Monte Carlo Localization (AMCL) are widely used because they can fuse odometry with range observations.

Peavy et al. [9] showed that AMCL robustness can be improved when map information is updated to reflect non-structural objects, illustrating the importance of maintaining a map consistent with the real operating environment.

For motion planning, the present work uses a layered approach. A* provides a global route over a grid map, while a local planner reacts to obstacles near the robot. Fox et al. [4] proposed DWA as a velocity-space method that evaluates dynamically admissible translational and rotational velocity pairs. Borenstein and Koren [5] demonstrated that histogram-based obstacle representations can support fast reactive avoidance. Hossain et al. [6] integrated modified DWA with a gap-following strategy for dynamic environments; Yang and Teng [7] combined an enhanced DWA with improved A*; and Kobayashi et al. [8] used Q-learning to adapt DWA weights under varying congestion. Together, these works support a hybrid architecture that separates long-horizon route generation from short-horizon collision avoidance.

A gap remains between algorithm-level studies and full system evaluation for warehouse deployment. Many papers report path-planning performance but do not connect navigation accuracy to mission completion, travel time, safety stops, and operational success. The methodology developed here therefore evaluates the robot at the mission level while still recording navigation-specific indicators. This creates a direct link between robotics performance and warehouse automation objectives.

Methodology

1. System Design

The proposed platform is a differential-drive AMR with two independently driven wheels and passive caster support. Differential drive was selected because it provides zero-radius turning, simple kinematics, and good maneuverability in narrow aisles. A 2-D LiDAR mounted above the chassis supplies 360-degree range data, wheel encoders provide incremental odometry, and a six-axis inertial measurement unit improves heading estimation during turns and wheel slip. An onboard computer executes localization, planning, and supervisory logic, while a motor controller closes the wheel-velocity loops. The nominal footprint is 0.62 m x 0.48 m, allowing the robot to operate in 1.2-1.5 m warehouse aisles with a safety margin.

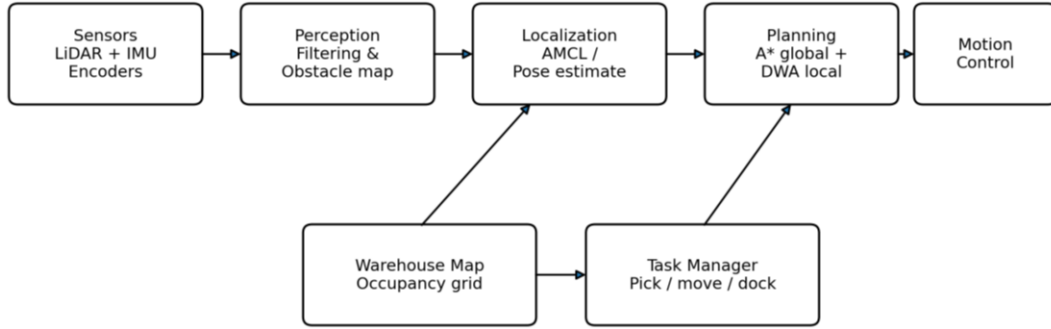
Table 1. Proposed AMR design and evaluation parameters

Subsystem / Parameter	Selected value	Purpose
Drive	Differential, 2 powered wheels	Tight turning and simple control
Primary ranging	2-D LiDAR, 10 Hz	Mapping and obstacle detection
Odometry	Quadrature wheel encoders	Short-term motion estimation
Inertial sensing	6-axis IMU	Heading-rate stabilization
Map	0.05 m occupancy grid	Global localization and routing
Global planner	A*	Minimum-cost grid route
Local planner	DWA	Dynamic collision avoidance
Nominal speed	0.8 m/s	Warehouse transport operation
Safety clearance	0.35 m	Slow-down / stop threshold
Evaluation missions	60 total	20 missions per scenario

2. Navigation Architecture

Figure 1 shows the information flow. Raw LiDAR ranges are filtered and inserted into a local obstacle representation. Wheel odometry and IMU data predict motion, while AMCL corrects the pose by comparing LiDAR observations with the occupancy grid. The global planner receives the current pose and a warehouse task goal, producing a grid path. DWA then samples feasible

velocity commands over a short horizon and scores them according to progress toward the global path, obstacle clearance, and forward velocity. The motion controller converts the selected linear and angular velocity into left- and right-wheel commands. A safety layer has authority over all motion commands and reduces or cancels velocity if the measured obstacle clearance is below threshold.

**Figure 1.** Layered control architecture of the proposed warehouse AMR.

3. Kinematic and Planning Model

The robot state is $q = [x, y, \theta]^T$. For linear velocity v , angular velocity ω , and sample period Δt , the differential-drive kinematic update is $x(k+1) = x(k) + v \cos(\theta) \Delta t$, $y(k+1) = y(k) + v \sin(\theta) \Delta t$, and $\theta(k+1) = \theta(k) + \omega \Delta t$. The global occupancy grid treats shelving and fixed structures as occupied cells and inflates them by the robot radius plus a safety margin. A* selects the global path by minimizing $f(n) = g(n) + h(n)$, where $g(n)$ is accumulated travel cost and $h(n)$ is a Euclidean heuristic. At the local level, DWA considers only velocity pairs that satisfy motor limits and allow stopping before collision [4]. The score J combines path alignment, obstacle clearance, and forward speed. Recent DWA research shows that changing these weights can improve performance in dynamic congestion [6]–[8]; therefore, the present methodology increases

the clearance weight when obstacle density within 2 m rises above a threshold.

4. Experimental Scenarios and Metrics

Evaluation was implemented as a seeded 2-D simulation so that each mission can be repeated. The warehouse environment contains parallel rack rows, cross aisles, pickup stations, a charging zone, and temporary obstacles. Twenty start-goal missions were executed for each of three conditions: (S1) static aisles with fixed racks and pallets; (S2) mixed traffic with slow moving obstacles crossing aisles; and (S3) dense dynamic traffic with more frequent crossings and temporary aisle blockage. The random seed was fixed at 42. Each mission ended successfully when the robot entered a 0.20 m goal radius before the time limit; collision or timeout was counted as failure. A scripted fixed-route AGV was included as an operational baseline. The baseline followed pre-defined aisle centerlines and stopped whenever its route was blocked,

whereas the AMR could replan around blocked segments.

Five primary metrics were recorded: (1) path length in meters, (2) mission time in seconds, (3) mean localization error in meters, defined as Euclidean distance between estimated and simulated ground-truth pose, (4) success rate, and (5) collision rate. Secondary observations included stop count and replanning events. Because the goal is methodology validation rather than hardware certification, the reported values are simulation outcomes and should not be interpreted as physical-robot safety certification.

Results

Table 2 summarizes the 60 AMR missions. In static aisles, all 20 missions were completed, with a mean path length of 29.8 m and mean mission time of 37.7 s. In mixed traffic, the success rate was 95% and localization error remained below 0.08 m. Dense dynamic traffic increased detours, stops, and local replanning, producing the longest average mission time, yet the robot still completed 90% of missions. No collisions occurred in the static or mixed scenarios, while the dense scenario produced a small collision rate associated with failed missions. These results indicate graceful degradation rather than abrupt failure as obstacle density increased.

Table 2. Simulation-based performance of the proposed AMR

Scenario	Path (m)	Time (s)	Loc. error (m)	Success (%)	Collision (%)
Static aisles	29.8	37.7	0.050	100	0.0
Mixed traffic	36.0	47.4	0.069	95	0.0
Dense dynamic	44.2	61.7	0.091	90	5.0

The operational comparison with the fixed-route baseline shows the main advantage of autonomy under obstruction. The baseline was competitive in an empty aisle, but its mission time increased sharply when crossings or temporary blockages forced repeated stops. Figure 2 compares mean mission time. The proposed AMR required 47.4 s in mixed traffic versus 63.5 s for the baseline, a reduction of 25.3%. In dense dynamic traffic, the AMR required 61.7 s versus 78.4 s, a reduction of 21.3%. The difference is produced by local avoidance and global replanning: the AMR can trade a small increase in distance for a larger reduction in waiting time.

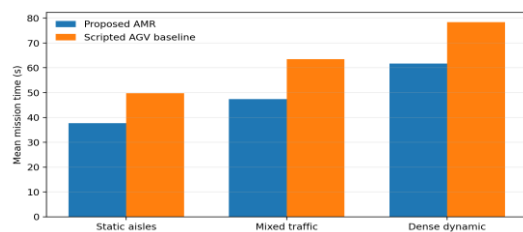


Figure 2. Mean mission time for the proposed AMR and fixed-route AGV baseline.

Localization accuracy also remained stable enough for aisle-scale navigation. Mean position error increased from 0.050 m in static aisles to 0.091 m in dense dynamic traffic. This trend is expected because moving obstacles temporarily occlude rack features and reduce the fraction of LiDAR returns that correspond to the static map. The result is consistent with the motivation of Peavy et al. [9], who showed that indoor localization benefits when map information reflects changes in the environment. For practical

deployment, dynamic-object filtering and periodic map maintenance should therefore accompany AMCL.

Conclusion and Discussion

The study developed a complete methodology for a warehouse AMR using a differential-drive base, LiDAR-encoder-IMU sensing, occupancy-grid localization, A* global routing, DWA local planning, and safety supervision. The design follows the broader shift from centrally controlled AGVs toward more adaptive AMRs described in intralogistics literature [1], [2]. The navigation stack also combines established probabilistic mapping concepts [3] with velocity-space collision avoidance [4] and later improvements intended for dynamic environments [6]-[8]. The simulation evaluation suggests that the architecture is suitable for flexible warehouse transport. Across 60 missions, the robot maintained sub-0.10 m mean localization error and retained high task-completion rates as traffic complexity increased. The largest operational benefit appeared when routes were temporarily blocked: the AMR could reroute instead of remaining stopped on a fixed guide path. This reduced mission time relative to the scripted AGV baseline while preserving a low collision rate. The results also reveal the expected trade-off between speed and safety. Dense traffic caused more detours and stop events, which increased mission time but limited collision exposure. Several limitations must be addressed before industrial deployment. First, the evaluation is simulation-based; wheel slip, LiDAR

reflections, uneven floors, payload shift, battery voltage, and wireless latency require hardware-in-the-loop and physical tests. Second, the study considers one robot; multi-robot fleets require traffic management, task allocation, deadlock handling, and charging coordination. Third, the safety layer is a research mechanism rather than a certification claim. Future work should validate the platform under recognized industrial mobile-robot safety procedures, evaluate human-aware speed control, and compare adaptive planners using common warehouse benchmarks. A further extension is to integrate semantic map updates such as those studied by Peavy et al. [9], allowing the navigation system to distinguish long-lived layout changes from temporary obstacles. Overall, the methodology provides a compact and reproducible foundation for designing and evaluating an autonomous mobile robot for warehouse automation.

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