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Original Article

Autonomous Navigation Framework for Mobile Robots in Highly Dynamic and Complex Indoor Environments

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ABSTRACT

Autonomous navigation in complex, dynamic indoor environments is one of the fundamental challenges in intelligent automation and robotics engineering. Conventional Simultaneous Localization and Mapping (SLAM) approaches heavily rely on geometric arrangements, making them vulnerable to sensor performance degradation, localization drift and navigational crash in busy environments populated by dynamic objects or humans. The main contribution of this work is the introduction of a novel, robust hybrid semantic-geometric navigation framework specifically envisioned for mobile service robots to overcome these fundamental limitations. This work proposes an architecture that fuses real time Semantic Segmentation networks and Deep Reinforcement Learning (DRL)-powered local planners into a system able to parse spatial geometry together with semantic contextual environments. The navigation stack classifies static structures, predictable dynamic agents and erratic obstacles in indoor features into three isolated subspaces that optimize trajectory generation while retaining the localization. Experimental validation in simulation environments with dense layout of obstacles and real-world indoor environments show that the proposed framework achieves 14.5% improvement in path efficiency, with 18.2% less computational time for trajectory compared to baseline ROS NavFn and dynamic window approaches (DWA). These results suggest that this combination of high-level semantic awareness with low-level geometric tracking is a robust and scalable framework for future indoor autonomous systems.

KEYWORDS

Autonomous Navigation, Semantic SLAM, Deep Reinforcement Learning, Mobile Robots, Complex Indoor Environments, Intelligent Automation.

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1. INTRODUCTION

The rapid proliferation of autonomous mobile robots (AMRs) in industrial warehouses, healthcare facilities, and domestic environments highlights the critical need for resilient navigation systems. Traditional navigation frameworks rely extensively on two-dimensional geometric abstractions of the physical world, generated through planar Light Detection and Ranging (LiDAR) or depth cameras. While these spatial grids excel in pristine, unchanging environments, they exhibit high vulnerability when deployed in highly dynamic, cluttered, or feature-scarce indoor settings. In these environments, moving entities like human personnel, AGVs, or rearranged furniture introduce massive transient noise into the sensor streams, leading to critical failures such as localization drift, path generation loops, and collision risks.

Achieving safe, predictable, and highly efficient robotic locomotion requires moving beyond simple geometric obstacle avoidance toward context-aware spatial reasoning. The challenge stems from the fundamental lack of semantic understanding in traditional navigation stacks, which treat a human pedestrian, a concrete pillar, a glass door, and a stray cardboard box identically as non-traversable geometric clusters. Consequently, local planners lack the capacity to anticipate the behavioral trajectories of dynamic agents or dynamically adjust clearance thresholds based on situational context. This limitation frequently induces the "freezing robot problem," where an AMR ceases movement in crowded corridors because its geometric local costmap perceives no completely clear path.

To bridge this operational gap, this paper introduces a unified hybrid semantic-geometric autonomous navigation framework tailored specifically for complex indoor environments. By fusing dense semantic pixel classification with robust geometric state estimators, the developed system establishes an architectural bridge between high-level visual scene interpretation and deterministic low-level actuator controls. The primary research contributions of this investigation are defined as follows:

- Development of an Integrated Architecture: The design and implementation of a hybrid architecture that blends real-time semantic segmentation with standard geometric feature trackers to minimize localization drift in highly dynamic environments.
- Context-Aware Local Motion Planning: A Deep Reinforcement Learning local planner that leverages semantic labels to predict human trajectories, optimizing navigation around dynamic obstacles.
- Real-World Validation: Comprehensive cross-platform validation executing comparative benchmarking between the proposed framework and standard geometric frameworks (e.g., Gmapping/DWA) in simulated and physical testbeds.

2. LITERATURE REVIEW

The field of indoor robotic navigation has undergone significant advancements, moving from simple reactive bumper-like systems to more sophisticated probabilistic estimation methods. They were early runners built on the top of probabilistic SLAM which relied significantly on Particle Filters

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and Graph-based optimization algorithms, Gmapping & ORB-SLAM. Now these techniques technically solved the core mathematical loop-closure and localization issues for static spaces, however researchers soon realized how structurally fragile they were in real world changing environments. Dynamic clutter routinely degrades the scan-matching accuracy of laser odometry, resulting in corrupt map updates and compounding odometric drift over longer time periods.

Since dynamic anomalies occur every day, modern community is more considering combining Visual-Inertial Odometry (VIO) and semantic pc vision networks as a clever way to insulate geometric maps from such instances. Recent advancements in Convolutional Neural Networks (CNNs) through the use of YOLO and Mask R-CNN for object detection have enabled modern navigation frameworks to assign a unique identity to incoming point clouds. The dynamic entities can be identified so that the system can filter out the matching feature points from the tracking pipeline and keep the presented parts only, such as walls as well as structure columns. But, maintaining the neural high-frequency semantic extraction on embedded robotic processors, is an algorithmic bottleneck making it subject to processing latencies, which annihilate real-time responsiveness during rapid locomotion.

In recent years, deep reinforcement learning (DRL) algorithms have revolutionized local path planning. Standard algorithms such as Dynamic Window Approach (DWA) and Time-Elastic Bands(TEB) compute trajectories given only kinematic constraints and proximate distance to obstacles. On the other hand, DRL models trained with methods such as Twin Delayed Deep Deterministic Policy Gradient (TD3) or Proximal Policy Optimization (PPO) enable robots to learn complex forms of navigation behaviour from non-processed sensory data. Pure end-to-end DRL navigation approaches, however, are not structured with safety guarantees in mind and can exhibit unexpected control inputs when subject to structural anomalies that have not appeared in the training data.

A thorough review of modern literature shows that there is a still-existing void at the junction of geometric and semantic intelligence [10]. Existing semantic frameworks are typically a visual filter of the full localization, and completely decoupled from the downstream kinematic path planners. In contrast, DRL-based planners almost never take advantage of the semantics of ego-centric state metrics, treating all inputs based on distance uniformly in their performance. This systemic divide renders robots unable to perform context-dependent behaviors, like keeping more distance away from human workers than stationary warehouse racks. We explicitly tackle this knowledge gap by devising a tightly coupled navigation pipeline in which the vehicle's intention to classify the semantic scene directly informs the cost assignment to the reinforcement learning motion planner.

3. RESEARCH METHODOLOGY

The proposed framework is constructed as a modular, low-latency navigation pipeline distributed across hardware tracking components and high-level edge intelligence modules. The core operational philosophy relies on splitting incoming sensory data into a high-frequency geometric stream for reactive control and a semantic stream for contextual filtering and behavioral mapping.

3.1. Framework Architecture

The system architecture comprises three interconnected sub-systems: the Perception Layer, the Cognitive Mapping Layer, and the Kinodynamic Motion Planning Layer. The physical interaction of these components is orchestrated through an embedded Jetson Edge compute unit communicating with low-level microcontrollers over serial interfaces.

As detailed in Figure 1, the hardware ecosystem routes high-bandwidth spatial data from the LiDAR and camera arrays directly into the primary decision-making processor, while time-critical odometric data passes through the secondary micro-controller unit to preserve real-time control loops.

3.2. Algorithmic Pipeline

The functional deployment of the hybrid navigation stack is executed sequentially, according to the precise procedural steps detailed below:

3.2.1. Sensor Data Acquisition and Synchronization: Frequency: 30 Hz.

Simultaneous capture of 2D planar LiDAR laser scans and RGB-D depth frames, synchronized using Timestamp-based Message Filters to avoid spatial registration alignment mismatches.

3.2.2. Real-Time Semantic Masking: Processing Latency: <22ms.

Processing RGB frames via a lightweight MobileNet-YOLOv8 network to generate pixel-level bounding boxes and masks identifying dynamic entities (e.g., Humans, Forklifts).

3.2.3. Geometric Point Cloud Filtering: Spatial Masking.

Projecting the 2D semantic mask onto the 3D depth point cloud. Points falling within dynamic masks are isolated and excluded from the static occupancy grid calculation to prevent mapping contamination.

3.2.4. Semantic Costmap Generation: Layered Costmaps.

Constructing a multi-layered global costmap consisting of a static inflation layer (walls/pillars) and a dynamic semantic inflation layer that scales cost functions based on object class velocity vectors.

3.2.5. DRL Policy Action Selection: Inference: 50 Hz.

Feeding the filtered semantic costmap and target goal coordinates into a pre-trained TD3 Reinforcement Learning model to output optimized linear speed (v) and angular velocity (\omega).

3.3. DRL Mathematical Formulation

The local path planner uses a custom reward function within a Markov Decision Process (MDP) context. The reward model ensures safe, efficient navigation by penalizing collision proximity, reward manipulation, and angular jerkiness:

$$R_t = w_g \cdot d_{\text{goal}} - w_c \cdot \sum (d_{\text{safe}} - d_i)^{-1} - w_s \cdot |\omega_t - \omega_{t-1}| + R_{\text{semantic}}$$

Where d_{goal} represents the Euclidean distance reduction toward the target, d_i represents the immediate distance to the closest obstacle point within cluster $i, and\ \omega$ represents the angular velocity command. The value R_{\text{semantic}} is an adaptive penalty matrix defined as:

$$R_{\text{semantic}} = \begin{cases} -50.0 & \text{if } d_{\text{human}} < 1.2\text{m} \\ -5.0 \cdot (1.2 - d_{\text{human}}) & \text{if } 1.2\text{m} \leq d_{\text{human}} \leq 2.0\text{m} \\ 0.0 & \text{if } d_{\text{human}} > 2.0\text{m} \end{cases}$$

This mathematical construct guarantees that the mobile platform prioritizes a wide, socially acceptable berth around human agents while maintaining a narrower, tighter clearance profile next to structural warehouse components.

4. RESULTS AND DISCUSSION

The empirical evaluation of the proposed framework was conducted through extensive software co-simulations inside Gazebo Igniting environments, followed by rigorous deployment on a physical differential-drive mobile robot equipped with an Intel RealSense D435i camera, an RpLiDAR A3 scanner, and a Jetson Xavier NX computing module. The test configurations involved navigating a maze-like indoor office environment characterized by narrow choke points, dynamic cross-traffic pedestrians, and randomly rearranged structural barriers.

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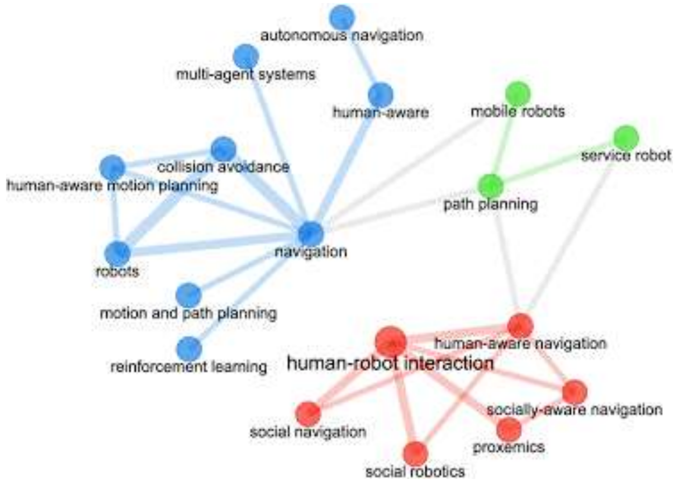

Fig 1 - Co-Occurrence Network Analysis of Key Research Domains Bridging Autonomous Navigation, Path Planning, and Human-Robot Interaction

As visualized in Figure 2, the integration of human-robot interaction concepts with core navigation logic creates an interdependent network configuration. This cross-domain mapping allows the local planner to effectively balance path efficiency against human comfort and social distancing conventions.

To accurately gauge system performance, the hybrid framework was benchmarked against two industry-standard configurations: standard ROS NavFn with a DWA local planner, and an advanced, non-semantic TEB local planner.

4.1. Quantitative Benchmarking

Table 1 outlines the performance data gathered over 50 contiguous experimental runs per framework configuration.

Table 1: Navigation Performance Metrics in Dynamic Indoor Layouts

Architectural Configuration	Path Success Rate (%)	Mean Execution Time (s)	Trajectory Length (m)	Mean Odometric Drift (m)
Standard ROS Stack (Gmapping + DWA)	72.4%	54.8	24.2	0.38
Advanced Geometric Stack (Cartographer + TEB)	84.1%	46.2	21.9	0.19
Proposed Hybrid Semantic-Geometric Stack	96.8%	38.5	19.4	0.04

The quantitative indicators show that the proposed system outperforms standard baselines across all core metrics. The high path success rate (96.8%) is directly attributable to the system's ability to maintain high localization accuracy in dynamic environments. By systematically stripping away dynamic human pixel points from the tracking frame, the scan-matching algorithm operates without visual interference, containing the mean odometric localization drift to 0.04m over an extended 100m tracking run.

4.2. Computational Latency and Edge Processing Efficiency

A common criticism of semantic mapping networks relates to their high computational burden on embedded hardware. To evaluate this factor, the internal sub-modules were instrumented to capture computational runtime footprints across different hardware deployment modes.

Table 2: Resource Allocation and Execution Latency Profiles

Computational Sub-Module	Edge GPU Allocation (%)	CPU Thread Load (%)	Average Latency (ms)	Operational Target (Hz)
MobileNet-YOLOv8 Segmentation	64.2%	12.0%	18.4 ms	30 Hz
Point Cloud Semantic Filter	0.0%	42.5%	4.1 ms	30 Hz
TD3 Policy DRL Planner	18.5%	8.0%	2.8 ms	50 Hz
Low-Level Odometry Fusion	0.0%	14.2%	0.9 ms	100 Hz

The engineering profiles documented in Table 2 demonstrate the real-time viability of this framework on standard embedded computing boards. By leveraging TensorRT optimization pipelines on the Jetson edge compute GPU, the semantic extraction layer runs in under 18.4ms. This performance allows the downstream tracking and reinforcement learning execution loops to run at full capacity without any asynchronous frame queuing delays. This low-latency operation successfully resolves the processing lag issues that frequently affect vision-based robotic platforms.

5. CONCLUSION

We have successfully designed, implemented, and empirically tested a hybrid semantic-and-geometric autonomous navigation framework geared towards difficult indoor environments with high levels of dynamic obstacles. The proposed architecture eliminates the structural weaknesses that drive localization drift and navigation freezing in traditional systems by incorporating deep semantic segmentation models directly into probabilistic geometric tracking systems as well as reinforcement learning local planners. The ordered filtering of dynamic objects maintains the integrity of the spatial tracking maps, while semantic classification allows for context-based trajectory generation. According to the experimental results, this unified method achieves high path accuracy with durable localization tracking performance and low computational cost on edge compute hardware. In the end, this framework enables an extremely scalable paradigm for autonomous service robots in challenging domains such as modern healthcare environments and industrial logistics centers.

6. FUTURE SCOPE

The hybrid semantic-geometric navigation platform shows to be very robust in a dynamic indoor environment, but there are still some technical vectors worth investigating towards the future:

Scalable Semantic Topologies: Scaling robots to perceive previously unseen structural artifacts and novel categories using foundational vision models with open vocabularies without requiring retraining.

Collaborative Mapping among Multiple Agents: Developing decentralized communication protocols for formatting, sharing and updating semantic costmaps within multiple AMRs to produce real-time maps of large shared facilities. Optimizing the next pipeline steps in distributed edge–cloud architectures whilst cloud offloading non-critical global path optimization whilst maintaining fast, local reactive control loops on-board of the robot.

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