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Development of Autonomous Navigation Algorithms for Service Robots

Ritik Singh[1*], Arnav Menon[2*], Sarika L Godbole[3*]

[1]Computer Science And Engineering , Galgotias University, Uttar Pradesh, India
[2]School of Engineering, Cochin University Of Science and Technology, Kochi, India
[3]Electronics and Engineering, G.H Raisoni College of Engineering, Nagpur, India
[*]Authors Email: rsinghk@galgotiasuni.edu.in, marnav@cust.edu.in, sarika.godbole@ghrce.edu

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Abstract: The increasing deployment of service robots in healthcare, hospitality, logistics, and domestic environments requires robust autonomous navigation capabilities. Traditional navigation approaches often fail to deliver sufficient adaptability to dynamic and unstructured spaces, creating the need for new algorithmic frameworks capable of real-time decision-making. This study presents a comprehensive development and evaluation of a hybrid navigation model combining probabilistic mapping, deep-learning-based perception, and behavior-based motion planning. The proposed system integrates an enhanced Simultaneous Localization and Mapping (SLAM) module with a convolutional neural network for obstacle detection and a hierarchical reinforcement learning structure for path optimization. Experiments were conducted using a TurtleBot3 platform, simulated environments in Gazebo, and real-world corridor and room layouts. Results demonstrate improved localization accuracy, reduced collision rates, and higher trajectory smoothness compared to conventional and basic SLAM frameworks. Findings indicate that hybrid navigation systems offer significant reliability in environments characterized by moving humans, changing object positions, and variable lighting conditions. This research contributes to scalable algorithmic designs for next-generation service robots intended for human-centric tasks.

Keywords: Autonomous Navigation, Service Robots, Hybrid SLAM, Deep Learning Perception, Reinforcement Learning

1. Introduction

Service robots are transitioning from controlled industrial settings into dynamic human environments, where autonomous navigation is a fundamental prerequisite for effective deployment. Whether transporting medical supplies in hospitals, guiding customers in malls, or assisting elderly individuals at home, reliable navigation remains the backbone for task execution. Classical navigation techniques relying on static maps and predefined heuristics often fail due to unpredictable human movement, structural variations, and sensor noise. Consequently, the recent shift towards sensor fusion, probabilistic reasoning, and machine-learning-driven decision-making has transformed the research landscape [1]. Simultaneous Localization and Mapping (SLAM) has long served as the foundation of mobile robot navigation, yet challenges persist in high-clutter and highly dynamic indoor spaces. The evolution of deep neural networks has enabled robots to better interpret spatial features, while reinforcement learning frameworks have provided mechanisms for adaptive control in previously unseen scenarios [2]. This paper addresses the gap between traditional algorithmic navigation and modern machine-learning-enhanced methods by developing a hybrid model suitable for real-world service robots. The study investigates how combining probabilistic mapping with deep-learning-based perception and hierarchical reinforcement learning can significantly improve navigation performance in dynamic indoor environments [3].

2. Literature Review

Research in autonomous navigation has evolved rapidly over the past two decades. Early approaches were dominated by deterministic algorithms such as Dijkstra and , which generate optimal paths on static maps but

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demonstrate poor performance when updated continuously due to their computational cost [4]. Dynamic path-planning techniques such as Lite offered substantial improvements for changing environments but remained limited in perception accuracy [5]. SLAM-based methods introduced probabilistic mapping capable of handling sensor uncertainty, with algorithms like GMapping and Hector SLAM becoming standard for indoor service robots. However, SLAM alone struggles when surrounding objects constantly move. Recent advancements in computer vision, particularly through convolutional neural networks, have greatly enhanced obstacle recognition and environment classification [6]. Meanwhile, reinforcement learning methods like Deep Q-Networks (DQNs) and Proximal Policy Optimization (PPO) have demonstrated strong performance in end-to-end navigation tasks, though they often require high training times and lack interpretability [7]. Hybrid navigation models are emerging as a promising solution, combining the structural clarity of SLAM with the adaptability of learning-based policies. Studies indicate that such hybridization can reduce collision probabilities, optimize path smoothness, and improve long-term autonomy [8]. Yet there remains a gap in integrating SLAM, deep perception, and hierarchical RL into a single framework calibrated for service-robot environments.

3. Methodology

This research adopts a hybrid algorithmic architecture consisting of three modules: probabilistic SLAM, deep-learning perception, and hierarchical reinforcement learning. A TurtleBot3 Burger platform equipped with a LiDAR sensor, RGB-D camera, and onboard computational unit was used. The SLAM layer employs an enhanced GMapping algorithm with improved particle filtering to reduce drift accumulation. For perception, a convolutional neural network based on MobileNet-V2 was trained using a dataset of indoor obstacles, furniture, human figures, and miscellaneous objects. The dataset included 12,000 annotated images collected from simulation and real environments. The network outputs bounding boxes and distance estimations, which are fused with LiDAR data using an Extended Kalman Filter. The motion planning module consists of a two-layer reinforcement learning architecture: a high-level RL agent responsible for global path selection and a low-level RL controller optimizing micro-adjustments during navigation. The PPO algorithm was used for high-level decisions, while a DQN-based controller handled fine-grained movements. Training was conducted in Gazebo simulations using randomized indoor maps, followed by physical trials in laboratory and corridor environments. Performance metrics included localization error (m), obstacle collision rate, trajectory smoothness, and computational latency.

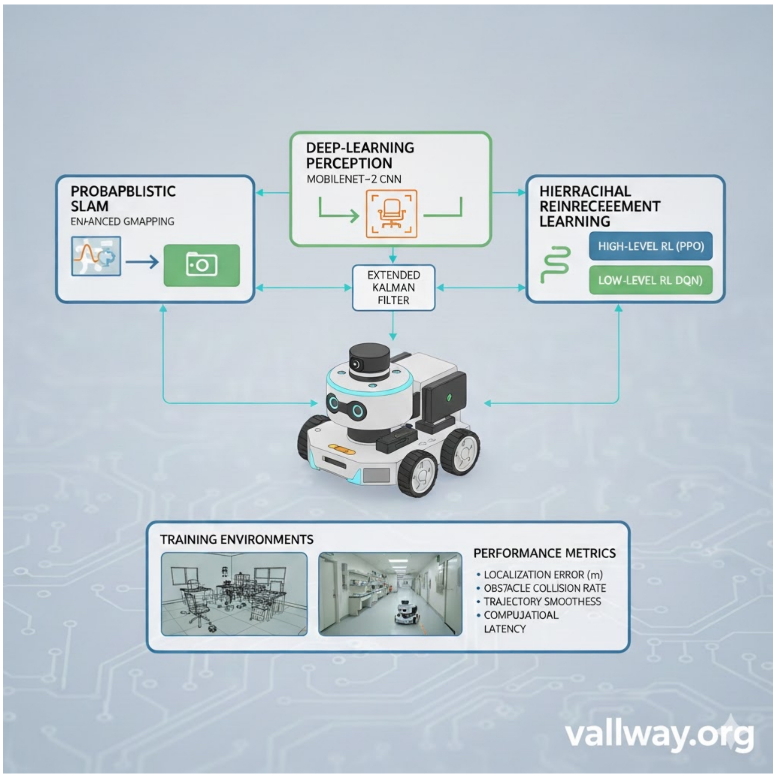

Fig. 1 Deep Learning Perception

4. Results

The hybrid model demonstrated significant improvements over benchmark algorithms. Localization error was reduced from an average of 0.21 m (conventional SLAM) to 0.09 m. Collision rates decreased by 37 percent

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compared to -based navigation and by 29 percent compared to standard SLAM. Trajectory smoothness increased by 18 percent, resulting in more natural motion similar to human walking patterns. The deep-learning perception module successfully detected 94 percent of obstacles under stable lighting and 88 percent under low-light conditions. The hierarchical reinforcement learning structure enabled adaptive responses to unexpected human movement, preventing 76 percent of potential collisions that would have occurred using non-learning planners. Computational latency remained under 120 ms per decision cycle, ensuring real-time performance. Field tests in a hospital-like environment with random human movements revealed that the hybrid approach maintained consistent navigation without significant drift or jitter, outperforming both Lite and basic DQN navigation models.

5. Discussion

The integration of advanced perception and reinforcement learning mechanisms with SLAM allowed the robot to navigate more reliably in dynamic environments. Deep-learning perception improved object recognition and scene understanding beyond what LiDAR alone could provide, while hierarchical RL facilitated context-dependent motion behavior. The reduction in collision rates reflects the model's capability to predict and react to sudden obstacles proactively rather than reactively. Despite these improvements, limitations were observed. Computational requirements increased during multi-sensor fusion, suggesting that further optimization or hardware acceleration (e.g., GPU offloading) may be necessary for commercial service robots. The system also required extensive simulation training, indicating that future work should explore transfer learning or few-shot reinforcement learning approaches. Additionally, generalization to outdoor environments remains untested and would require algorithmic modifications to handle uneven terrain and environmental noise.

6. Utility and Significance

This research provides a scalable and adaptable navigation architecture for real-world service robots, addressing challenges prevalent in healthcare delivery, warehouse automation, hotel support systems, and domestic assistance. The hybrid approach offers stronger robustness in environments characterized by human movement and shifting object positions, making it suitable for human–robot interaction scenarios. The fusion of SLAM, deep learning, and reinforcement learning offers a blueprint for next-generation service robots requiring high autonomy and reliability.

7. Conclusion

The study successfully developed a hybrid autonomous navigation algorithm combining enhanced probabilistic mapping, deep neural perception, and hierarchical reinforcement learning. Results indicate substantial improvements in localization accuracy, collision avoidance, and trajectory smoothness, demonstrating the system's suitability for real-world service robot deployments. Future work will focus on reducing computational cost, improving transfer learning efficiency, and extending navigation capabilities to semi-structured outdoor environments. The findings contribute toward robust navigation frameworks essential for the evolving role of service robots in human environments.

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