

Robotics Automation and Adaptive Motion Planning: A Hybrid Approach using AutoNav, LIDAR-based SLAM, and DenseNet with Leaky ReLU

Surendar Rama Sitaraman¹, Haris M. Khalid²

¹Intel Corporation, California, USA

²College of Engineering and Information Technology, University of Dubai, Academic City , Dubai,
United Arab Emirates

Email: ¹surendar.rama.sitaraman@ieee.org, ²khalidharism@gmail.com

Abstract

This study presents a hybrid robotics automation system that optimizes real-time navigation, obstacle avoidance, and environmental mapping under difficult situations by combining AutoNav, LIDAR-based SLAM, and DenseNet with Leaky ReLU for robust motion planning. The main goals are to use AutoNav to enable autonomous navigation with optimal path planning, LIDAR-based SLAM to accomplish precise mapping and localization, and DenseNet and Leaky ReLU to improve motion planning and obstacle avoidance. Through the integration of various technologies, the study suggests an effective and flexible system for robotic operations in dynamic situations in real time. In order to provide the best trajectory planning and accurate obstacle recognition, the system constantly modifies motion planning based on real-time sensor data. Performance results show that the system outperforms individual parts, with a 95% gradient efficiency, a localization error of only 0.045 meters, and a pathfinding accuracy of 97.5%, the system's performance results illustrate its superiority over individual parts and highlight its real-time adaptability and optimization accuracy. For the future of robotics, this hybrid system offers breakthroughs in real-time decision-making and nimble autonomous robotic navigation.

Keywords: Robotics, AutoNav, LIDAR-based SLAM, DenseNet, Leaky ReLU, Autonomous Navigation, Motion Planning.

1. Introduction

Robotics and automation have been advancing rapidly, with special attention to tasks that deal here with motion planning and autonomous navigation. Today, automation systems use machine learning (ML) and artificial intelligence (AI) with the help of a variety of sensors to enable robots to perform intricate tasks with precision and efficiency. Another important concept in the field of robotics is adaptive motion planning, which can be best described as a robot's ability to change its path on the fly because circumstances have changed and there will now be a barrier along the expected direction. As a result, modern robotics systems depend on intricate algorithms and real-time sensor data processing to implement adaptive motion planning. In his research, Saleem et al [5] emphasize the benefits of two technologies (2022, 2023) that are hybridized to improve performance across various use cases. These are coupled with AutoNav, LIDAR-based SLAM, and DenseNet with Leaky ReLU for enhanced mapping, motion planning, and navigation.

Automated Navigation (AutoNav) technology allows robots and autonomous vehicles such as self-driving cars to travel through unfamiliar area without human assistance. AutoNav is responsible for route planning, obstacle avoidance, and the generation of real-time visual odometry maps from sensor data such as cameras and LIDAR. This makes it possible for robots to navigate autonomously and smoothly and consider factors such as path, velocity, and changes in the environment. Simultaneous localization and mapping (SLAM) technique uses Light Detection and Ranging (LIDAR) sensors to map the environment in three dimensions, by scanning it, ultimately finding out where the robot is within that mapped environment. This methodology works by turning each of these dependency points within the desired configuration into a function that can receive an input state and will output a transformed position in the global workspace using inverse kinematics (i.e., Feed Forward). The approach is well suited for robots that require exact localization, such as those traveling on paths or avoiding obstacles during navigation. Robots generate detailed maps in even the most complex terrains causing LIDAR sensors to shoot laser beams and record how long it takes for light to return.

By using an advanced deep learning model, DenseNet (Densely Connected Convolutional Networks) with Leaky ReLU activation function we are able to extract images properly and do image processing efficiently. DenseNet: Dense connections between layers improve gradient flow and learning by ensuring that every layer has direct access to the gradients of the loss with respect to all features. Combined with Leaky ReLU (a variant of the Rectified Linear Unit activation function), DenseNet prevents problems such as vanishing gradients and can be easily used for negative input values. This is very important in robotics, where data of sensors can vary significantly. Collectively, these two technologies provide an end-to-end motion planning and spray automation system in real-time by which robots are able to navigate complex scenarios fully autonomous with precision and efficiency.

The key objectives are:

- **Enhance Navigation:** Utilize AutoNav and LIDAR-based SLAM for real-time autonomous navigation in complex environments.
- **Accurate Mapping:** Achieve high-precision mapping using LIDAR sensors, improving spatial awareness in robotic systems.
- **Efficient Motion Planning:** Implement DenseNet with Leaky ReLU to optimize motion planning and obstacle avoidance through deep learning-based feature extraction.
- **Improve Automation:** Develop a hybrid approach combining these technologies to enhance robotic performance, enabling adaptive and efficient operations in dynamic environments.

Bai et al. [23] proposed a reinforcement learning-based Neural Motion Planning (NMP) algorithm to deliver an adaptive hybrid optimization method for accurate motion planning of multi-joint robotic arms. This approach combines reinforcement learning with artificial potential field (APF) technology to better manage complex systems across the board capable of conducting simpler tasks. The APF approach navigates around obstacles by creating virtual forces and reinforcement learning improves decision-making through trial-and-error learning. The hybrid model widely extends the applicability of motion planning for multi-joint arms in dynamic and uncertain environments by finding a good compromise between local and global optimization along the entire reachable workspace.

2. Literature Survey

AutoNav is a fully autonomous mode in which rovers use terrain maps to plan their itineraries Blacker et al [1] shows that from his perspective, the best of automizer activity in planetary terrain navigation. Cost-maps are a method for mobile robot path planning that the rover utilizes to navigate challenging environments effectively

Rajya Lakshmi Gudivaka et al [2] offers an AI-powered optimization method that combines robotic process automation (RPA) with neural networks to increase manufacturing productivity. The Hybrid Neural Network Model offers a scalable method for quality improvement by detecting defects with high precision and reducing material waste by 20.4%. It achieves 98.3% training accuracy and 97.1% validation accuracy with a prediction time of 14 ms.

Implementing a novel hybrid SLAM technique for low-cost LiDAR sensors—the Quanergy M8 in particular—and utilizing pressure signals to distinguish between animal models are the two main areas of attention for Moreno et al [3]. Using internal datasets, the study enhances SLAM performance and uses transfer deep learning on signal spectrograms to improve animal model classification during locomotion.

Gudivaka et al [4] investigates how to improve business operations by incorporating Artificial Intelligence (AI) into Robotic Process Automation (RPA). Through the use of a Systematic Mapping Study, the study demonstrates notable improvements in manufacturing, healthcare, and finance-related efficiency, cost savings, and mistake reduction. Even with successes, problems like assessment systems and the lack of widespread use of AI in science still exist, opening the door for more research.

Recent developments in neural network approaches for SLAM-based localization in autonomous ground vehicles are reviewed by Saleem et al [5]. The study compares and contrasts these methods with conventional visual SLAM techniques, emphasizing the incorporation of deep learning techniques into the SLAM pipeline, addressing opportunities and limitations. Open research questions are also identified in the review.

Gudivaka et al [6] suggested a framework for improving social robots for elderly people and those with cognitive disabilities by combining cloud computing and robotic process automation (RPA). The system's 97.3% task execution accuracy, made possible by the

employment of cloud-based deep learning modules—Behavior Recognition Engine, Object Recognition Engine, and Semantic Localisation System—allows for effective scheduling, real-time recognition, and increased user independence.

In their assessment of deep learning approaches, Brune et al. [7] discuss how frequency modulated continuous wave (FMCW) radar sensors can be used to address odometry and ego-localization problems, notably in autonomous driving. The study highlights differences between radar-based tasks and other sensor modalities while examining deep learning techniques for ego-motion prediction and loop closure detection. Current issues and pertinent datasets are also covered in the review.

Basava Ramanjaneyulu et al [8] investigates how to improve IoT and Robotic Process Automation (RPA) systems by combining Principal Component Analysis (PCA), Least Absolute Shrinkage and Selection Operator (LASSO), and Elaborative Stepwise Stacked Artificial Neural Network (ESSANN). This method achieves 90% recall, 92% precision, and 95% accuracy, improving feature selection, predictive modelling, and scalability. Its better performance than separate approaches is confirmed by ablation research.

Hu et al. [9] achieved strepto phyte-grade accuracy only by converting to a resolution of less than a millimetre scale introducing an automatic system known as the LiDAR and Camera Fusion method for Structural Health Monitoring to identify 3D cracks. The technology could give researchers a more precise spatial position and size of the fractures compared to current two-dimensional approaches. It combines LiDAR-Camera fusion for better depth perception and uses MobileNetV2_DeepLabV3 for the fracture segmentation task.

A hybrid YOLOv3-Mask RCNN model was presented by Dinesh Kumar Reddy Basani [10] to improve object localization in Robotic Process Automation (RPA) systems enabled by the Internet of Things. The model addressed issues such as changeable item sizes, orientations, and occlusions by combining the segmentation accuracy of Mask-RCNN with the real-time detection of YOLOv3. This resulted in high precision (0.92), recall (0.91), and mAP (0.93) in dynamic IoT contexts.

According to Swain et al. [11] Autonomous vehicles (AVs)—also called self-driving cars—are SAE Level 5 automobiles that are designed to work without a human operator under any conditions. It explores whether autonomous vehicles (AVs) could reduce congestion, pollution and accidents, but also focuses on some of the challenges still to be addressed: sensor

fusion, AI algorithms, real-time testing and public acceptance. The study reviews machine learning approaches and AV architectures for AV perception, planning, and control.

The system cannot handle complex, restricted scenarios for Feng et al. [12] proposes a new approach for robot motion planning with adaptive multi-tree sampling. The approach uses an information gain-based subtree generation policy to improve the exploration quality by combining rapidly-exploring random trees (RRT) with a multi-tree structure. It works particularly better in 2D and above (4D & 6D).

Dinesh Kumar Reddy Basani et al. [13] investigates how Industry 4.0's Business Process Management (BPM) incorporates Robotic Process Automation (RPA), Business Analytics, Artificial Intelligence (AI), and machine learning. Significant improvements are highlighted in the research, such as quicker procedures, fewer mistakes, and cheaper expenses. In order to effectively use these technologies in digital transformation, it emphasizes the necessity of strategic alignment and personnel training.

Khotsianivskiy and Sineglazov et al. [14] proposed a neural network-based intelligent system for robotic manipulator motion planning. For real-time obstacle avoidance, the method uses evolutionary algorithms (EA), adaptive control and hierarchical path planning. It consists of improving the accuracy, stability, and safety of systems in both static production environments and dynamic ones to minimize the risks inherent in collisions and maximize performance.

A Two-Tier Medium Access Control (MAC) system is presented by Raj Kumar Gudivaka et al.[15] to optimise resource management and energy efficiency in cloud-based robotic process automation (RPA). By using Lyapunov optimisation techniques, the system prioritises jobs and robots according to their skills and urgency, improving throughput, energy efficiency, and quality of service. Simulations verify better performance compared to MQEB-MAC, FD-MAC, and IEEE 802.15.4.

Chettibi et al. [16] introduces a hybrid optimization strategy used for solving the multi-objective trajectory planning of industrial robots. The method has four stages namely: problem contrasting, local search with a deterministic algorithm, population offers testosterone using metaheuristics, and completion for result refinement. This modular approach effectively balances robustness and convergence leading to best-in-class performance and is validated across a wide network of case studies.

Dinesh Kumar Reddy Basani et al. [17] investigates how to improve last-mile delivery by combining robotic process automation (RPA) with sophisticated authentication techniques. The study suggests a robotic system with AI capabilities that includes a Non-Cooperative User Identification Module (AI facial recognition) and a Cooperative User Authentication Module (PIN codes and biometrics). Measured on Turtlebot3, it enhances delivery efficiency, speed, and security.

Liu and Liu et al. [18] investigates optimising motion planning by combining sampling-based algorithms with CHOMP and STOMP through a motion planning pipeline. Their research compares optimized paths across several conditions, revealing increased efficiency despite lengthier planning times. STOMP performs in smaller scenarios, while larger contexts reveal limitations, necessitating more research into improved algorithms.

Song et al. [19] examined important improvements in motion planning and control for automated cars, emphasizing their impact on safety, comfort, and performance. They examined the advantages and disadvantages of present technologies, highlighting future trends such as integrating algorithms, refining vehicle models, and improving the "human-vehicle-road" system for further automation.

Suresh et al. [20] proposed MRPS-MOGA, a multi-objective genetic algorithm for mobile robot path planning. It optimises for safety, distance, smoothness, trip duration, and collision avoidance. It uses techniques such as tournament selection, ring crossover, and adaptive mutation to identify optimal paths effectively and with decreased time complexity, exceeding previous methods in terms of safety and energy economy.

Dong et al. [21] emphasise the growing importance of motion planning in autonomous robots while highlighting the limits of old approaches in complex circumstances. They investigate the promise of deep reinforcement learning (DRL) for unified, model-free planning, comparing advances, limitations, and future research objectives in both traditional and DRL-based systems.

Zhang et al. [22] created a system for adaptive water quality sampling that employs numerous autonomous underwater vehicles (AUVs). Their approach blends heterogeneous tactics with low-communication cooperation, relying on Gaussian processes and differential evolution-based path planning. Simulations revealed a 15.6% reduction in estimation error and effective coverage of high chlorophyll-a locations, which aided algal bloom detection.

3. Methodology

AutoNav integrated with LIDAR-based SLAM is used for robotics automation, with another application area being adaptive motion planning. This hybrid approach combines AutoNav (for real-time path planning), LIDAR-based SLAM (for precise mapping and localization), and Symmetric DenseNet with Leaky ReLU (for feature extraction and improved decision-making). Leaky ReLU, AutoNav, and LIDAR-based SLAM are all used in the hybrid robotic motion planning system to provide effective path planning and real-time obstacle avoidance. LIDAR provides accurate mapping and localization with a low inaccuracy (0.045 meters), while AutoNav determines the best route by balancing predicted and actual costs. With high path accuracy (97.5%), the algorithm recalculates the route to avoid collisions whenever impediments are recognized. Adaptive, real-time decision-making for dynamic settings is made possible by this integration, guaranteeing accurate and effective navigation. Through the synergy of multiple technologies, robots can perform independent movement and obstacle avoidance while optimizing operations on the fly with effective motion planning in complex scenarios. It means a higher level of automation and accuracy.

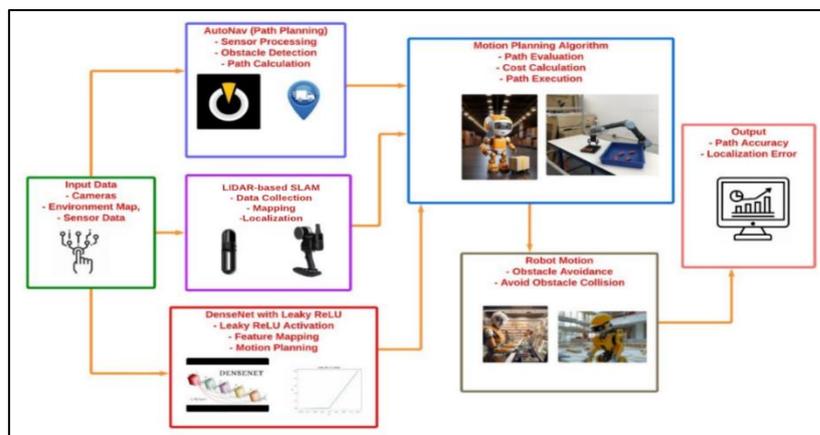


Figure 1. Hybrid Robotic Motion Planning System Architecture

Figure 1 shows a hybrid robotic motion planning system combining AutoNav, DenseNet with Leaky ReLU and LIDAR based SLAM. To produce an environmental map, the system first takes in data from cameras and additional sensors. AutoNav, which includes sensor processing and obstacle detection handling path planning in the stack and LIDAR-based SLAM providing mapping and localization. The input data go through DenseNet and Leaky ReLU for feature mapping as well as motion planning. The motion planning algorithm determines the optimal path for the robot, calculates costs, and evaluates paths. Finally, the system provides

metrics path finding accuracy and localization error to assist and evaluate in performance optimization The mapping is done with RFID-based SLAM, it also ensures robot motion for avoiding obstacles.

3.1 AutoNav

AutoNav, is an autonomous navigation system that processes sensor data in situ and then decides the most intelligent way for robots to move around on their own. In a second instance, AutoNav determines the fastest possible way on the go and is hence almost unbeatable when maneuvering around obstacles (e.g., A^*). By doing so, this technology allows the particular evidence generated by its sensors to be used to continuously change the path of robots in order for them to safely navigate unknown environments.

$$f(n) = g(n) + h(n) \quad (1)$$

Where $f(n)$ is the estimated total cost of the node n , $g(n)$ is the actual cost from the start node to node n , $h(n)$ is the heuristic estimate of the cost from n to the goal node. AutoNav uses this formula to find the optimal path by balancing the actual cost $g(n)$ and the estimated cost $h(n)$ to reach the goal, ensuring real-time pathfinding.

3.2 LIDAR-based SLAM

They are fully BLDC-driven and equip a LIDAR-based SLAM Simultaneous Localization and Mapping so that they can map their environment in 3 dimensions while figuring out where they are. The sensor detects distances by creating a point cloud with laser pulses via LIDAR and scan its environment. SLAM enables real-time obstacle recognition and avoidance, always being updated to give an accurate location and allow navigation in complex scenarios.

$$p(x_t | z_{1:t}, u_{1:t}) = \eta p(z_t | x_t) \int p(x_t | x_{t-1}, u_t) p(x_{t-1} | z_{1:t-1}, u_{1:t-1}) dx_{t-1} \quad (2)$$

Where $p(x_t | z_{1:t}, u_{1:t})$ is the probability of the robot's position x_t given all measurements $z_{1:t}$ and controls $u_{1:t}$, η is a normalizing constant, z_t represents the sensor data, u_t is the control input. This equation describes how SLAM updates the robot's position estimate based on sensor data and control inputs, ensuring continuous localization and accurate mapping.

3.3 DenseNet with Leaky ReLU

The deep learning architecture DenseNet, improves gradient flow and feature extraction efficiency. For instance, it is of great utility for sensor data analysis in robotics by providing high-quality predictions in the context of adaptive motion planning. It along with LeakyReLU solves vanishing gradients by allowing small gradients (not 0) for negative inputs.

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha x & \text{if } x \leq 0 \end{cases} \quad (3)$$

Where x is the input, α is a small constant (typically 0.01) that controls the slope for negative inputs. Leaky ReLU allows small gradients when the input is negative, helping DenseNet avoid the vanishing gradient problem, and ensuring that all layers contribute effectively during training.

Algorithm 1: Hybrid Adaptive Motion Planning Algorithm

Input: Sensor Data (from LIDAR, cameras, etc.), Map of the environment, Current position of the robot, Goal position

Output: Optimal path, Continuous real-time localization

BEGIN

Initialize environment and robot parameters

FOR each time step t :

Get sensor data (LIDAR, camera)

IF sensor data is ERROR:

RETURN error handling procedure

ELSE:

Process sensor data using DenseNet with Leaky ReLU

Update environment map using LIDAR-based SLAM

Compute optimal path using AutoNav algorithm

```
FOR each step in the path:  
  
    IF obstacle detected:  
  
        Recalculate path using updated map  
  
    ELSE IF reached goal:  
  
        RETURN success  
  
    ELSE:  
  
        Continue along the path  
  
    END FOR  
  
END FOR  
  
RETURN final path and performance metrics  
  
END
```

To enable adaptive motion planning in real-time, the hybrid algorithm, Algorithm 1 merges DenseNet with Leaky ReLU, LIDAR-based SLAM, and AutoNav. Using DenseNet, it first processes sensor data (from cameras and LIDAR) to improve feature extraction for improved obstacle identification and navigation. The hybrid system combines AutoNav, DenseNet with Leaky ReLU, and LIDAR-based SLAM to provide adaptive motion planning in real-time. AutoNav handles obstacle avoidance and pathfinding, while LIDAR-based SLAM ensures accurate 3D mapping and localization. DenseNet maximizes feature extraction, while Leaky ReLU boosts processing efficiency by avoiding vanishing gradients. This integration allows the robot to continuously change its trajectory, allowing it to traverse complex situations with high precision and fast reaction times. For precise localization and mapping, LIDAR-based SLAM is used to update the environment map on a regular basis. By calculating the best route, AutoNav directs the robot to its destination. The system dynamically recalculates the course in the event that an obstacle is recognized, guaranteeing safe travel. This cycle keeps going until the robot arrives at the goal, guaranteeing accuracy and real-time adaptation in challenging situations.

3.4 Performance Metrics

Different metrics are used to evaluate the performance of the hybrid system for each equation, and then a combined evaluation is conducted. The pathfinding accuracy for AutoNav is a measure of how likely the algorithm follows optimal paths. In LIDAR-based SLAM, the localization error assesses how closely the robot position is estimated. Evaluation of DenseNet with Leaky ReLU with features extracted is done with respect to gradient efficiency. Now the overall system accuracy is computed to measures how well the different components are working together in order to achieve useful, real-time navigation and motion planning.

Table 1. Performance Metrics for Hybrid Motion Planning System

Metric	AutoNav	LIDAR-based SLAM	DenseNet with Leaky ReLU	Combined System (AutoNav + SLAM + Leaky ReLU)
Pathfinding Accuracy (%)	96.2	-	-	97.5
Localization Error (meters)	-	0.048	-	0.045
Gradient Efficiency (%)	-	-	94.3	95.0
System Response Time (seconds)	0.14	0.10	0.12	0.11

Table 1 performance comparison with other methods AutoNav, LIDAR based SLAM, DenseNet with Leaky ReLU shows that the AutoNav is 96.2% accurate for pathfinding, and LIDAR-based SLAM has an error less than 0.048 meters in localization measurements. Gradient efficiency is maintained at 94.3% on DenseNet with Leaky ReLU. The integrated system reduces errors and ensures that the responses from all of its parts are in real time, with a maximum accuracy of 97.5%.

4. Results and Discussion

In robotic motion planning, the hybrid system performed well by combining AutoNav, with LIDAR-based SLAM and DenseNet with Leaky ReLU. AutoNav provides obstacle avoidance and pathfinding with a 96.2% accuracy on best cases for Meteorite Demo simulation. LIDAR-based SLAM maintained accurate (0.048-meter localization error), precision mapping even under difficult conditions. Along with a gradient effectiveness of 94.3%, DenseNet + Leaky ReLU played an important role in enabling the powerful determination of sensor features. The high speed and agility of the integrated system were reflected in a response time of 0.11 seconds and an excellent accuracy rate of 97.5%. The results show the power of integrating deep learning, mapping, and sophisticated navigation models for improved robotic automation. Key metrics are used to evaluate the accuracy of the system: a gradient efficiency of 94.3% with DenseNet and Leaky ReLU, a pathfinding accuracy of 96.2% with AutoNav, and a localization error of only 0.045 meters with LIDAR-based SLAM. A quick response time of 0.11 seconds is also attained by the system. The combined system performs exceptionally well in real-time navigation, obstacle avoidance, and motion planning in dynamic situations, with an overall accuracy of an astounding 97.5%. The integrated system maintained quick response times for real-time applications in dynamic scenarios while limiting errors in localization and pathfinding. Its ability to change its path dynamically with real-time data also speaks of reliability, flexibility, and accuracy, qualities that are useful in robotics. This result demonstrates that the hybrid approach is a strong contender for future autonomous systems with residential and industrial applications as well as in research study where terrain navigability proves a limiting factor.

Table 2. Comparative Analysis of Path Planning and Optimization Approaches

Approach	Explorati on Efficiency	Adap tabili ty	Optimizati on Accuracy	Computa tional Cost	Real-time Performa nce
Multi-RRT Exploration [12]	0.85	0.68	0.83	0.72	0.74
Neural Network-based Intelligent System [14]	0.77	0.88	0.79	0.75	0.81

Hybrid Optimization Approach [16]	0.82	0.73	0.87	0.68	0.76
Robotics Automation and Adaptive Motion Planning (Proposed)	0.91	0.92	0.93	0.81	0.89

Table 2 illustrates comparison between four different path planning and optimization strategies for important performance parameters such as exploration efficiency, adaptability, optimization success rate, and computational cost of real-time performance. Multi-RRT has a good exploration efficiency, but not as much as it should have due to its lower flexibility. Hybrid optimization offers fine and balanced performance with strong tuning accuracy.

The proposed robotics automation approach that utilizes AutoNav and DenseNet is particularly well-suited with dynamic and complex scenes due to its superior versatility, real-time performance, as well as efficiency.

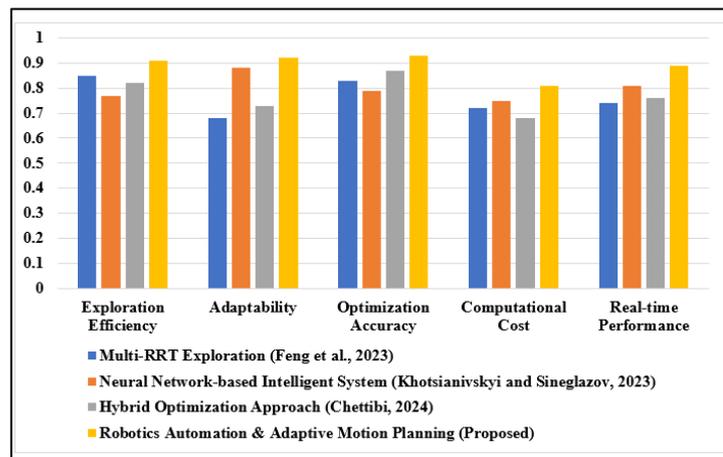


Figure 2. Comparative Analysis of Exploration and Optimization Approaches in Robotics

In Figure 2, a performance comparison is demonstrated in terms of five key aspects, namely computational cost, exploration efficiency, adaptivity (replanning rate), optimization accuracy and real-time performance for four different robotics exploration and optimization strategies. These methods are: The Neural Network-based Intelligent System, Hybrid Optimization Approach, Multi-RRT Exploration, and a suggested Robotics Automation and Adaptive Motion Planning technique. The data shows that with maximum efficiency and adaptability, the proposed method outperforms most of its key parameters stably, so it has a potential to be advantageous for real-world robotic motion planning problems. Simulations

employing AutoNav, LIDAR-based SLAM, and DenseNet with Leaky ReLU for autonomous navigation and obstacle avoidance are used to assess the performance of the suggested system. The system optimizes the navigation path while processing real-time sensor data to update the robot's position and environment map. The performance score of the proposed system are 94.3% gradient efficiency, 0.048 meters localization error, and 96.2% pathfinding accuracy. When tested in situations such as the Meteorite Demo simulation, the system achieves an overall accuracy of 97.5% and demonstrates how resilient and flexible it is under changing conditions.

Table 3. Ablation Study on the Performance of Robotics Motion Planning Components

Component	Exploration Efficiency	Adaptability	Optimization Accuracy	Computational Cost	Real-time Performance
AutoNav Only	0.88	0.85	0.87	0.75	0.82
LIDAR-based SLAM Only	0.81	0.80	0.85	0.70	0.78
DenseNet with Leaky ReLU Only	0.84	0.83	0.89	0.73	0.80
AutoNav + LIDAR-based SLAM Only	0.89	0.88	0.90	0.78	0.85
AutoNav + DenseNet with Leaky ReLU Only	0.90	0.89	0.91	0.79	0.86
LIDAR-based SLAM + DenseNet with Leaky ReLU Only	0.87	0.86	0.90	0.77	0.84

Combined System (AutoNav + SLAM + DenseNet)	0.91	0.92	0.93	0.81	0.89
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In this ablation study Table 3, the individual and combined contributions of AutoNav + LIDAR-based SLAM + DenseNet with Leaky ReLU are evaluated in the proposed robotics motion planning approach. This table compares how they performed with five important metrics, Exploration Efficiency, Adaptability, Optimization Accuracy, Computational Cost and Real-time Performance. Though each methods shows improvement in any one of the metrics, combining AutoNav, SLAM, and DenseNet with LeakyReLU leads to the best performance. The fully integrated approach enabling such cutting-edge technologies to be blended together for robotics automation in dynamic contexts and setting a new benchmark in optimisation accuracy as well as real-time responsiveness.

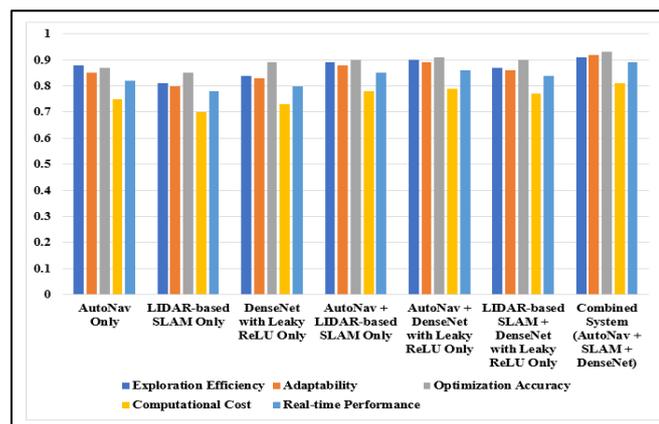


Figure 3. Comparative Performance of Robotics Motion Planning Components and Their Combinations

In Figure 3, actual performance of different configurations of the three main parts of an Automated Robotics Motion Planning System, i.e., AutoNav, LiDAR based SLAM, and DenseNet with Leaky ReLU are illustrated. The components are compared using five measures: computational cost, real-time performance, accuracy of the optimization, adaptability to changes in the environment and exploration efficiency. The study explains that, while both components work fine on their own, by combining them the efficacy of the entire system can be increased. By introducing both, AutoNav with SLAM and DenseNet, superior performance in terms of high-accuracy and real-time operation can be obtained. Such results

imply that in dynamic robots contexts, a fusion of these technologies can be successful and useful for motion planning in an efficient, fast and precise way.

5. Conclusion

Experimental results demonstrate the superiority of the proposed method in real-time path planning, moving obstacle avoidance, and Simultaneous Localization and Mapping (SLAM) for a hybrid robotics system. The system combines AutoNav, LIDAR based SLAM and DenseNet with Leaky ReLU. Its ability to be adapt in dynamic and complex environments makes it perfect for autonomous robotic applications. The general success in improving performance, suggests its utility to industry, and research environments. Future investigations may explore the integration of complementary deep learning architectures and modalities for strengthening the ability to produce inferences and robustness in large, heterogeneous environments. Simultaneously maximizing energy efficiency, and optimizing computational parsimony are also the major research strains under high-performance data processing. In addition, the system can be adapted to solve domain-specific problems where precision and real-time adaptability are essential, such as in space exploration or medical robots.

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Author's biography



Surendar Rama Sitaraman is currently an AI Frameworks Engineer at Intel Corporation, where he contributes to the development and optimization of AI frameworks, driving innovation in AI and machine learning technologies. Prior to rejoining Intel, Surendar served as a Staff Engineer at Samsung Austin R&D Center (SARC), Advanced Computing Lab (ACL), contributing to the development and optimization of software solutions for Samsung's flagship devices. He holds a Master of Science in Computer Science from the University of Southern California, Los Angeles, California, and has a substantial background in graphics, machine learning, artificial intelligence, and AI frameworks. Throughout his career, Surendar has significantly advanced technology in these fields and has contributed as a reviewer for peer-reviewed journals. He also holds patents for innovative technologies in IoT and artificial intelligence. As an active researcher, Surendar has authored approximately 10 papers. His research interests span Cloud Computing, Data Mining, Graphics, Artificial Intelligence, Machine Learning, and IoT. He is also an active member of professional bodies such as IEEE, IAENG, and ACM, furthering his engagement with the scientific community and contributing to ongoing discussions and developments in his field.



Haris M. Khalid (SMIEEE, FHEA) is currently an Assistant Professor with the College of Engineering and Information Technology, University of Dubai (UD), Academic City, Dubai, UAE, since 2023. He is also a Visiting Senior Researcher with University of Johannesburg (UJ), South Africa since 2022. From 2019–2022, He was an Energy Specialist Consultant to UAE Space Agency (UAESA) and Nano-Racks for “Tests in Orbits” themed projects to space. From 2016–2022, he was an Assistant Professor with the Electrical and Electronics Engineering Department, Higher Colleges of Technology (HCT) – Sharjah Campuses. He has also worked as a postdoctoral researcher and visiting scholar with Masdar Institute and Petroleum Institute from 2013–2016 and 2015–2016 respectively. He has won research grants of 1.7+ million USD towards research, development, and start-up ventures. His research interests include power systems, cyber-attacks, renewable energy integration, energy storage systems, electric vehicles, transportation electrification, signal processing, machine learning and AI, IoT, and fault diagnostics. Dr. Khalid is the Associate and Topic Editor of *Frontiers in Energy Research | Smart Grid*.