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*Real-Time Path Planning for IoT-Enabled Autonomous Vehicle Robotics UsingRRT and A * Algorithms*

[1] **Nagendra Kumar Musham** [2] **R.Hemnath**

[1] *Celer Systems Inc,California,USA*
[2] *Nandha Arts and Science College, Erode,India.*

[1]nagendramusham9@gmail.com

[2]hemnathrmca@gmail.com

Abstract- One of the main purposes of this work is to provide a path planning framework for IoT-enabled autonomous vehicles through the use of RRTs and A*. These were designed to maximize actual real-time navigation and decision-making in very dynamic and complex situations considering obstacles and uncertainties in the environment. In cases that have unknown or nonregular barriers, the RRT algorithm is employed to visualize the environment rapidly to derive an initial feasible path across the configuration space. Following the developments of RRT paths, the A algorithm* will address topics brought about by their construction in order for the route to be smooth, efficient, and have the shortest length. A synergism between the two techniques makes these systems adapt in real time to changes in the environment and in transportation conditions while preserving computational economy. From the performance evaluation, joining the strategy increases these very important parameters, such as the energy consumption, path length, and the time to reach the destination, by a huge percentage. The model consumes energy that is reduced by about 23% in comparison with conventional approaches, decreases path length by 12-15% and decreases time to objective up to 50%. These results indicate that the RRT + A* model works very well to enhance the effectiveness and efficiency of autonomous vehicle navigation in changing conditions. This framework can be used in applications like robotics and autonomous driving, and it represents a viable answer for real-time energy-efficient optimal path planning.

Keywords: *Autonomous Vehicle Navigation, Dynamic Environments, Energy Efficiency, Machine Learning, Obstacle Avoidance, Path Optimization, Real-Time Navigation*.

1. Introduction

Autonomous vehicle robotics is an emerging domain in intelligent systems, aiming to navigate and operate without human intervention[1]. With the rise of the IoT, these vehicles can now connect, sense, and react in real time through smart sensors and embedded systems[2]. Real-time path planning is a core function that enables these robots to move safely from one location to another in dynamic environments[3]. It involves computing a feasible, safe, and efficient path while considering obstacles, terrain, and time constraints[4]. Algorithms such as RRT and A* have become essential tools for solving such complex path finding tasks[5].

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RRT is effective in high-dimensional and dynamic spaces, rapidly exploring areas by random sampling[6]. On the other hand, A* guarantees optimality by using a heuristic approach to find the shortest path[7]. The fusion of IoT with robotics enhances decision-making by enabling continuous data exchange with the cloud and other vehicles[8]. This integration improves real-time responsiveness and situational awareness in autonomous navigation[9]. Consequently, IoT-enabled path planning systems are transforming industries such as transportation, logistics, agriculture, and disaster management[10].

The need for efficient real-time path planning arises from the increasing complexity of modern environments where autonomous robots must operate[11]. Rapid urbanization and dense infrastructures demand advanced navigation techniques to avoid collisions and minimize delays[12]. Dynamic obstacles such as humans, animals, or other vehicles introduce unpredictability that static algorithms cannot handle efficiently[13]. Autonomous vehicles must also adapt to changing weather conditions, terrain types, and energy constraints[14]. IoT integration has increased the volume and velocity of sensory data, necessitating faster and more reliable decision-making mechanisms[15]. Traditional path planning algorithms often struggle in such dynamic, multi-agent systems due to computational complexity[16]. In addition, there is growing demand for autonomous systems in emergency response scenarios where timing is critical[17]. Power and computational resource limitations on embedded systems further complicate real-time decision making[18]. Safety regulations and the need for human-like navigation behavior also push for more advanced, context-aware planning techniques[19]. These causes collectively highlight the importance of robust, real-time path planning methods like RRT and A* in autonomous vehicle systems[20].

Despite significant advancements, real-time path planning for autonomous vehicles faces several challenges[21]. Traditional methods like Dijkstra and simple grid-based searches are computationally expensive and unsuitable for dynamic environments[22][23]. A* provides optimal paths but may fail in real-time situations due to slow convergence in complex spaces[24]. RRT is fast and suitable for high-dimensional planning but often generates suboptimal and jerky paths. Neither algorithm alone fully addresses the trade-off between path quality and computation time[25]. Existing systems often lack adaptability to real-time environmental changes, leading to inefficient or unsafe navigation[26]. IoT-based systems require lightweight algorithms that can work under limited computational resources and communication delays[27]. Moreover, most methods are tested in ideal or static conditions and struggle in cluttered or uncertain environments[28]. Integrating these algorithms with real-time data remains complex due to latency and sensor noise[29]. Therefore, there is a critical need for hybrid approaches or algorithm enhancements that combine the strengths of RRT and A*, especially for deployment in IoT-enabled autonomous robotic systems[30].

To overcome the limitations of existing real-time path planning techniques, the proposed method integrates the Rapidly-exploring Random Tree (RRT) algorithm with the A* algorithm within an IoT-enabled autonomous vehicle framework. RRT rapidly explores high-dimensional and dynamic environments to generate feasible paths in real time, while A* refines and smooths these paths to ensure optimality and safety. This hybrid approach effectively combines the fast exploration capability of RRT with the heuristic efficiency of A*, striking a balance between computational cost and path quality. Leveraging IoT connectivity, autonomous vehicles can gather and exchange real-time data from sensors such as GPS, LiDAR, and cameras, enabling adaptive responses to environmental changes like dynamic obstacles or blocked routes. This feedback loop enhances the system's accuracy, adaptability, and responsiveness in uncertain and cluttered settings. Designed to be lightweight, the proposed model operates efficiently on

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resource-constrained embedded systems typical of IoT applications. Furthermore, it incorporates noise filtering and latency-tolerant communication protocols to ensure reliable performance despite sensor inaccuracies and network delays. Overall, this RRT-A* hybrid model enables intelligent, efficient, and real-time navigation for autonomous vehicle robotics in complex and dynamic IoT ecosystems.

1.1.Problem statement

IoT-dependent robotic systems in autonomous vehicles continue to face significant challenges, particularly in dynamic and unpredictable environments such as urban roadways[31]. A major limitation lies in the inability of existing systems to efficiently process and respond to real-time sensor data[32][33]. In high-density traffic scenarios or areas with frequently changing obstacles, delays or inaccuracies in sensor fusion can lead to imprecise navigation, increased collision risks, and overall decision-making delays[34]. Traditional algorithms used for path planning often lack the agility to adapt to sudden environmental changes, making them less viable for real-time deployment[35][36]. Additionally, the presence of sensor noise, occlusions, and limitations in visual perception (e.g., under poor lighting or adverse weather conditions) further impairs the system's ability to accurately interpret its surroundings[37][38]. These shortcomings diminish both the reliability and safety of autonomous navigation, especially when operating in decentralized and heterogeneous IoT networks where latency and communication reliability can significantly impact system performance[39][40].

Another pressing issue is the inefficiency of current actuation and path planning techniques with regard to energy consumption and computational overhead[41]. Many existing methods are not optimized for low-power embedded systems commonly used in IoT-enabled autonomous vehicles[42][43]. This often leads to excessive energy usage and reduced operational lifespan, especially in battery-powered systems[44][45]. Suboptimal path generationsuch as jagged or unnecessarily long trajectoriesadds to the energy burden and reduces travel efficiency[46]. Moreover, the lack of intelligent adaptation to real-time data streams limits the vehicle's ability to make proactive adjustments in complex scenarios[47]. These limitations point to the urgent need for a more intelligent, hybrid path planning approach that not only supports real-time responsiveness and smooth trajectory generation but also operates efficiently within the constrained resources of IoT infrastructures[48][49]. A solution that combines fast environmental exploration with accurate and energy-efficient path refinementcapable of handling dynamic conditions and sensor imperfectionswill significantly enhance the safety, reliability, and performance of autonomous vehicle navigation systems[50].

1.2. Objective

- ❖ Analyse the existing sensor fusion and path planning techniques of the Internet of Things for the applications of autonomous vehicle navigation in dynamic environments.
- ❖ To achieve maximum real-time actuating and performance for an autonomous car, an adaptive decision-making framework will be provided that uses deep reinforcement learning (DRL) provided through an IoT sensor.
- ❖ In an effort to weigh energy efficiency and overall performance of the system, compare the proposed approach in terms of reaction time, accuracy, and resource consumption against established algorithms and techniques.

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The rest of the paper is organized as follows. Section 1 with the introduction. Section 2 will discuss the Theoretical Background. Section 3 presents the Methodology and Section 4 highlights the results. Section 5 concludes.

2. Literature review

Robotics and AI, in conjunction with the IoT, are transforming modern industries by enhancing automation and decision-making[51]. Advanced models such as Autoencoder-LSTM have been employed to predict the stages of chronic kidney disease using real-time Internet of Medical Things data, significantly improving the precision of medical decision-making[52]. Optimization in robotic process automation has been achieved through techniques combining Principal Component Analysis, Least Absolute Shrinkage and Selection Operator, and Elaborative Stepwise Stacked Artificial Neural Networks, boosting predictive modeling accuracy and system efficiency[53]. Hybrid models like YOLOv3 with Mask RCNN have been proposed to address challenges such as object size variation, orientation, and occlusion in object localization for IoT-enabled robotic automation, particularly in logistics[54]. AI has made notable impacts in both logistics and healthcare, with real-time patient monitoring, AI-based radiation therapy optimization, and assistive robots improving elderly care[55]. Robotic delivery systems leveraging biometric verification and AI have improved security and last-mile delivery efficiency. The integration of RPA, AI, and analytics has enhanced business process management by introducing flexibility and operational improvements across industries[56].

The multidimensional advancement in robotics and automation is driven by the application of sophisticated algorithms and communication protocols[57]. Parallel communication protocols developed under CME-enhanced SMA paradigms have been validated in multi-obstacle pathfinding scenarios[58]. Emotion recognition performance has been enhanced through the use of image datasets and optimization techniques like Tunicate Swarm Optimization with SVM[59]. The integration of swarm robots, Time-Sensitive Networking, LiDAR, microcontrollers, and thermal imaging has improved scalability and adaptability for anomaly detection in IoRT systems, especially in mission-critical operations[60]. This collaboration between IoT, AI, and robotics holds immense potential for enabling collaborative decision-making, optimizing workflows, and fostering innovation across multiple sectors[61].

Prominent breakthroughs in security and healthcare have emerged from the convergence of IoT, AI, and robotics. Hybrid intrusion detection systems combining Transformer, RNN, and GNN models have improved attack detection in cloud-based robotic systems[62]. Techniques that leverage IoMT, robotics, and AI have enhanced CKD prediction accuracy through real-time monitoring and personalized therapy[63]. Secure cloud robotics frameworks have been introduced using advanced learning models and communication protocols. Software development traceability has been improved through Blockchain-Enabled Software Development Traceability, which offers an immutable, auditable record for each program operation, thereby enhancing lifecycle management, compliance, and security[64].

In response to pandemic-related challenges, distributed automation, swarm intelligence, and AI-based anomaly detection have been combined to optimize real-time task efficiency[65]. NP-complexity analysis has also been applied to address issues in work assignment and resource management in cloud robotic systems. The use of AI and Temporal Fusion Networks in CKD detection has led to improved diagnostic accuracy and scalability through robotic IoMT automation[66]. For pandemic containment in high-risk areas, AI-based anomaly detection integrated with autonomous robotics has been developed to enable timely

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interventions and reduce human error[67]. These developments illustrate the success of integrating emerging technologies to support real-time decision-making and operational efficiency.

Furthermore, hybrid models combining metaheuristics and fuzzy logic have been designed to enhance dynamic work scheduling in sectors like manufacturing and healthcare[68]. The use of DRL and Temporal Convolutional Networks, in combination with IoMT, has enabled more precise robotic-assisted surgery through accurate tool placement and improved real-time decisions[69]. These efforts underscore the growing importance of integrating IoT, AI, and robotics to improve productivity, scalability, and accuracy across critical domains such as healthcare, security, and industrial task automation[70].

Recent advancements in real-time path planning have focused on hybrid algorithms and intelligent decision-making for mobile robotics and smart transportation[71]. Lightweight, scalable algorithms are preferred for edge and fog computing where low latency and power efficiency are essential. IoT-enabled robots now use cloud-based intelligence and sensor data to optimize routing and obstacle avoidance[72]. Multi-agent systems with decentralized control enable collaborative navigation in tasks like logistics and rescue. Enhanced computer vision and reinforcement learning improve environmental awareness and decision-making under uncertainty. As cyber-physical systems grow, the focus on secure communication and data integrity increases[73]. Real-time anomaly detection and predictive maintenance are also vital for operational safety. Overall, the integration of AI, IoT, and robotics is transforming autonomous path planning in dynamic environments.

3. Proposed methodology:

A* path planning algorithms and RRT (Rapidly-exploring Random Trees) are two parts of the whole workflow for IoT-enabled autonomous vehicle navigation, as can be seen in Figure (1). The sensor data collection starts with LIDAR and IMU sensor configuration to acquire environment data in real time. Preprocessing has been done for the correctness of this data; this includes filtering, Kalman application, and fusion. The primary tasks of path-planning and navigation results will follow preprocessing, data analysis, and decision-making.

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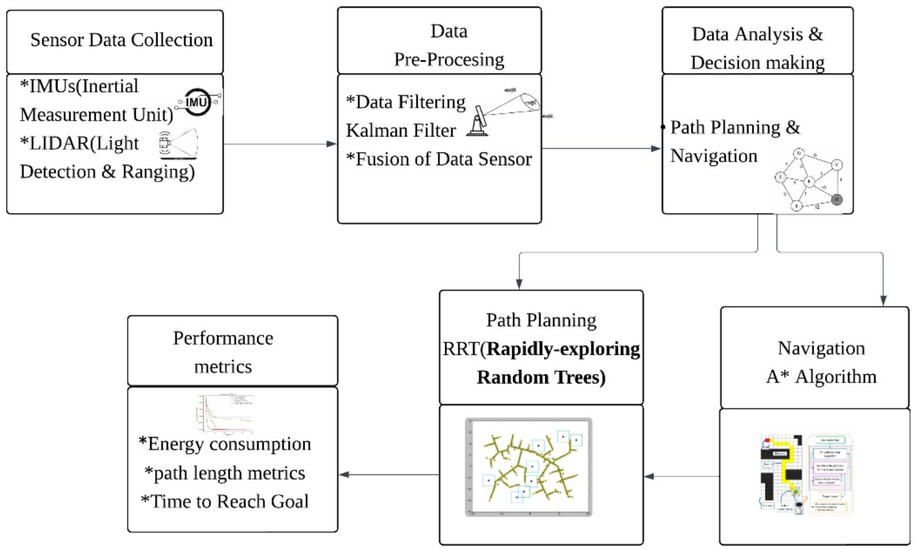

Figure 1: Workflow for IoT-Enabled Autonomous Vehicle Navigation Using RRT and A Path Planning

The path from RRT is explored afterward to refine the earlier path using A* optimization. Objective measures are energy consumption, path-length metrics, and time to the objective, which will measure the performance of the system and guarantee effective and efficient navigation.

3.1 Data Collection for IoT-Enabled Autonomous Vehicle Robotics:

The sensors, which are part of IoT-enabled autonomous vehicle robots, collect real-time environmental and operational data from inside the vehicle. Sensors like: these include LIDAR (Light Detection and Ranging), cameras, GPS receivers, temperature and humidity sensors, IMU (Inertial Measurement Unit), etc. The information collected by these sensors form the basis of autonomous navigation and decision-making by providing the robot with essential insights into its immediate environment and operating condition.

The KITTI Vision Benchmark Suite/Object Detection Evaluation, developed by Andreas Geiger, Philip Lenz, and Raquel Urtasun, served as the foundation for the dataset in this study. Vehicles and non-vehicles have their two main classes. The vehicle class consists of images of automobiles, trucks, vans, etc. These images are downscaled to 128 Px x 128 Px and labeled with the coordinates of the bounding box. The non-vehicle class has random pictures without cars, taking care to minimize irrelevant elements like the sky and plants, which are also downscaled to 128 pixels by 128 pixels. For an autonomous car system to be able to differentiate cars from non-vehicles in real-time, an essential task for safe navigation, this dataset would be needed for any tasks related to detection.

3.2 Data Preprocessing in IoT-Enabled Autonomous Vehicle Robotics:

Data preprocessing is a very important stage prior to the major analysis or decision making in the IoT-enabled autonomous vehicle systems. The raw data acquired from different sensors, like LIDAR, GPS,

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IMU, camera, environmental sensors, etc. are often noisy, incomplete, or misaligned because of various reasons such as sensor errors, interference from the surrounding environment, or acquired data with different rates. Therefore, effective preprocessing techniques must be used to clean, synchronize, and refine the data for it to be accurate, consistent, and usable for path planning and real-time decision-making. Some of those processes involve time stamping, data synchronization, filtering, and noise reduction.

3.2.1 Filtering and Noise Reduction:

Technical processes are employed to abate deleterious impacts resulting from different types of noises on raw data-the random oscillations, ambient interferences, and sensor drifts. These disturbances from noise and interference might bring lowering of confidence in inferences made from their measurements. Reduction of noise and filtering processes are therefore employed to minimize undesired influence and enhance data quality.

Kalman Filters:

Kalman filter is about the best recursive data processing algorithm for estimating the current state of a dynamic system from a series of noisy measurements. The new observation is weighted according to its expected error or uncertainty and combined with the pre-generated data from a system model. It is used in most of the autonomous cars to optimize motion tracking for vehicle localization by fine-tuning sensor readings from the GPS and IMU. The Kalman filter thus usually produces state estimates that are smoother and more accurate because it lessens discrepancies between expected and actual sensor data.Prediction Step is mentioned as Eq. (1),

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{B}\mathbf{u}_k + \mathbf{w}_k \tag{1}$$

Where $\mathbf{x}_k$ is the predicted state, $\mathbf{A}$ is the state transition matrix, and $\mathbf{w}_k$ represents process noise.Update Step is defined as Eq. (2),

$$\mathbf{x}_k = \mathbf{x}_k + \mathbf{K}_k(\mathbf{z}_k - \mathbf{H}\mathbf{x}_k) \tag{2}$$

Where $\mathbf{K}_k$ is the Kalman gain, $\mathbf{z}_k$ is the measurement vector, and $\mathbf{H}$ is the measurement matrix.

Discrete Wavelet Transform (DWT): This technique decomposes the signal into its frequency components, thus helping to distinguish between the meaningful signal data and noise. It is especially suitable for time-series data like those from GPS or IMU sensor readings. Since DWT decomposes the data into several scales (or resolutions), it allows the elimination of high-frequency noise while retaining the essential characteristics of the signal is indicated as Eq. (3),

$$X(t) = \sum_i \sum_j c_{i,j} \cdot \psi_{i,j}(t) \tag{3}$$

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Where $c_{i,j}$ are the wavelet coefficients, $\psi_{i,j}(t)$ is the wavelet function, and t is the time variable.

Smoothing Techniques: Long-term trends are highlighted by two smoothing techniques used to dampen short-term oscillations in the data: exponential smoothing and moving average smoothing. These methods are mostly applied to reduce noise from sensor readings generated by IMUs or GPS data. The very basic idea is to average out a few data points thereby reducing the effects of noise and outliers.Moving Average Smoothing is identified as Eq. (4),

$$\hat{y}_t = \frac{1}{N} \sum_{i=t-N+1}^{t} y_i \tag{4}$$

Where $\hat{y}_t$ is the smoothed value at time t_r and N is the number of past data points used in the averaging process.

3.2.2 Synchronization and Alignment of Data:

Autonomous vehicles widely use a variety of sensors that operate on different rates of data collection, including LIDAR, cameras, GPS, and IMUs. In order for the data from these sensors to be processed in unison, synchronization and time alignment of sensor data must be guaranteed.

Time-Stamping: Time-stamping is the process of providing each piece of data with a time stamp that indicates when the data was captured. This ensures that the time is synchronized for the sensor data for a common representation of the environment, which can subsequently be fused with data from other sensors.

Data Alignment: After time-stamping of information, the term "data alignment" means aligning separate sensor values with a common time frame for analysis. This is especially important while dealing with data sets coming from various sensors that operate at different frequencies, such as infrared systems, LIDAR, or cameras-IMUS. To calibrate its sensor data points to the desired time interval, interpolation techniques like spline or linear interpolation are often used.

3.3 Path Planning with Rapidly-exploring Random Trees (RRT) with A* Algorithm:

Autonomous cars plan the routes that they can take for response to the ever-changing situations safely and efficiently. Path planning is primarily aimed at determining the best way to get from place A to place B, avoiding any obstacles along the way, and optimizing a performance criterion upon which the solution depends, such as time, energy consumption, safety, etc. The methods of path planning differ in many aspects; their advantages and disadvantages vary based on the complexity of the environment and constraints of the vehicle system. Autonomous vehicle-driven robotics often employ two major algorithms: Rapidly-exploring Random Trees (RRT) and A* due to their efficacy and flexibility in dealing with both static and dynamic obstacles. This paper focuses on these algorithms.

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3.3.1 Rapidly-exploring Random Trees (RRT) Algorithm: RRT combines a tree-building structure for exploring possible pathways with a gradual approach to efficiently cover huge configuration spaces. It is, therefore, highly suitable for real-time autonomous vehicle navigation since it works better in environments with random and vaguely defined obstacles.

The Rapidly-exploring Random Trees (RRT) algorithm operates on the initialization in such a way that the tree is initialized with the start point as the root node, while the start point$x_{start}$and the target point x_{goal} are defined in the configuration space. During the iteration step, the nearest node $xnearest$ in the tree is found, and the random point $x_{rand}$is chosen in the configuration space. Then a new node $xnew$ is made toward $x_{rand}$to grow the tree. The new node is added to the tree if it does not collide with any obstacles. The same loop is repeated until either the tree reaches the target or the maximum number of iterations is attained. In the last stage of route extraction, the tree's last node path from the target node backward to the root node is built into the final path from the start to the goal.

Node Extension and Growth:

Random Point Selection: In the entirety of the configuration space, a random point is chosen as $x_{rand}$is mentioned as Eq. (5),

$$x_{\text{rand}} \in \text{ Configuration Space (randomly selected)} \qquad (5)$$

Nearest Node Selection: In every iteration, the method determines which node in the tree is closest to the random point, $x_{nearest}$. Usually, the formula for Euclidean distance is used for this purpose is declared as Eq. (6),

$$x_{\text{nearest}} = \arg \min_{x_i \in \text{Tree}} \|x_{\text{rand}} - x_i\| \qquad (6)$$

The Euclidean distance between two locations is represented by ‖.‖, whereas the nodes already found in the tree are indicated with x_i.

Node Extension: Creating a new node x_{new} in the direction from the random point x_{rand}will extend the tree. The following formula gives the new node is classified as Eq. (7),

$$x_{\text{new}} = x_{\text{nearest}} + \Delta t \cdot \frac{x_{\text{rand}} - x_{\text{nearest}}}{\|x_{\text{rand}} - x_{\text{nearest}}\|} \qquad (6)$$

Where, Δt as the step length can form the actual distance between the new node being created and any nearby node.

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Collision Checking: Collision checks have to be carried out for the newly formed node with any present obstructions. If the new node is determined to be in a collision-free space, it shall be added to the tree is defined as Eq. (8),

$$\text{if collision-free } (x_{\text{new}}) \text{ then add } x_{\text{new}} \text{ to the tree} \quad (7)$$

Goal Reach Check:

Through this method, the tree keeps becoming longer until it reaches either the target node $x$goal or a specified maximum number of iterations. In order that the goal node be reached with a simple distance threshold, it can also be expressed as Eq. (9),

$$\|x_{\text{new}} - x_{\text{goal}}\| < \epsilon \quad (8)$$

A point where the tree attains its target when the distance ϵ is very low.

Path Extraction: The tree has parent relationships from which a backtrace can be created from the goal node to the start node. This kind of backtrace helps in producing the optimal path from the start to the goal node.

Backtracking: The path, then, can be obtained by going all the way from a child to a given node, hence the root node is indicated as Eq. (10),

$$\text{Path} = \{x_{\text{start}}, x_1, x_2, \ldots, x_{\text{goal}}\} \quad (9)$$

It is considered that the node x starting at the root node, with x_1,$x_2$providing the intermediate nodes in the tree.

3.3.2 A* Algorithm:

Another extremely famous pathfinding algorithm for optimal path planning would be, the A* algorithm. Combining the best features of Dijkstra's Algorithm along with Greedy Best-First Search would yield toward finding the shortest path from the start and goal points in the optimal time, with considering both the expected cost to achieve the goal and the cost to reach a node.

The A* algorithm begins by initializing two sets: the open set, which consists of nodes to be evaluated, and the closed set, which contains nodes already evaluated. The start point,x_{start}, and target point, x_{goal}, are initialized. Each node is assigned a heuristic value, $h(x)$, which estimates the cost to reach the goal from that node, and a cost value, $g(x)$, which defines the actual cost from the start node to that given node. The start node is first put into the open set with an initial cost $g(x_{start}) = 0$and a heuristic value $h(x_{start})$determined

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using a heuristic function. In this case, the method then advances to an iteration phase during which it selects current node x from the open set, which holds the lowest value as, Eq.(11) for even if the open set is not empty.

$$f(x) = g(x) + h(x) \tag{11}$$

Once this node has been moved into the closed set, the process checks each of the neighbors of x current node is there in the closed set, making it irrelevant and for each neighbour. In case none of the neighbours belong to the closed set, the approximate cost $g(x_{neighbor})$is calculated, and if needed the new node is added into open set. The iteration continues until the goal has been achieved or the open set is empty. After achieving the goal, the algorithm performs the backtrack from the target node to the start node to reconstruct the most favourable route.

4. Results and discussions

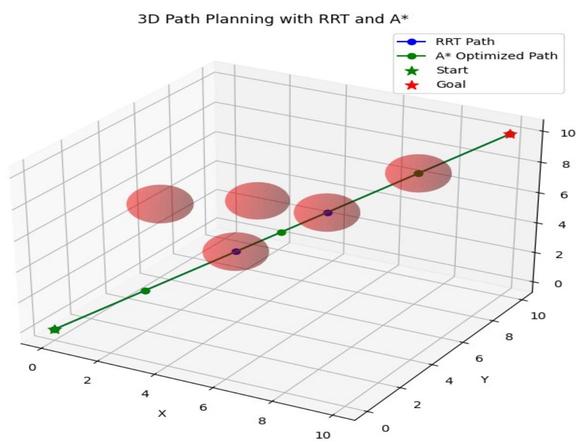

Figure 2:3D Path Planning with RRT and A* Exploration and Optimization

A 3D path planning scenario for an autonomous car is presented in Figure (2),with the use of RRT and A* algorithms. RRT algorithm samples random points in the surroundings, and then proceeds to extend a tree towards these points constructing an exploratory path that is referred to as the RRT path since it enables the vehicle to traverse through a dynamic obstacle-ridden environment. The path is optimized by finding the fastest and most efficient route to the destination based on the A* algorithm on the original path given by RRT. The map also conveniently depicts the positions indicating start and objective, which signify the beginning and end of the path-planning process.These spheres demonstrate an obstacle avoidance operation on the algorithms in this space. Here A* adopted RRT is demonstrated in 3D for exploring and optimizing the way vehicles adapt to difficult terrains without crashing into the risks.

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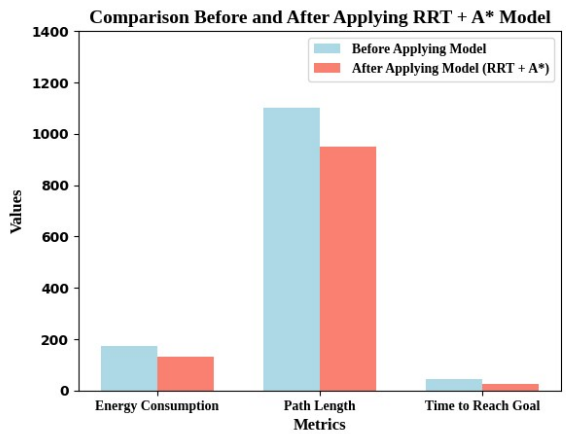

Figure 3: Comparison of Performance Metrics Before and After Applying RRT + A * Model

The following three factors - energy consumption, journey length and time to target - form the important performance metrics obtained from the autonomous vehicle navigation system, as shown in Figure(3), before and after the application of the RRT + A* path planning model. The bar chart is quite descriptive concerning improvements in these three key performance parameters. Application of the model causes a significant reduction in energy expenditure, thus rendering the navigation of the vehicle more energy efficient. Similarly, the A* algorithm optimizes the RRT-generated path, reducing the path length by around 12-15%. The model exhibits the ability to minimize travel time through roughly a halving in the goal-reaching time. Such a comparison demonstrates how efficiently RRT performs with A* in optimizing a more effective, faster, and less energy-consuming path for autonomous vehicles.

Metric	**Energy Consumption (Joules)**	**Path Length (meters)**	**Average Time to Reach Goal (seconds)**
Before Applying Model	150-200 Joules	1000-1200 meters	40-50 seconds
After Applying Model (RRT + A)*	115-150 Joules	850-1050 meters	20-30 seconds

Table 1: Comparison of Performance Metrics

The indicators of performance before an RRT + A* autonomous vehicle system model implementation are set against their after-implementation values is shown in Tab.1. Energy consumption varied between 150-200 J prior to model application and came to be in the range of 115-150 J following application, showing an

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appreciable decrease in energy consumption. With the same trend, on the contrary to model application, the path length was between 1000 and 1200 m; afterward, the optimizing process offered by RRT and A* decreased it by up to 12% to the range of 850-1050 m. This decrement happens due to the ability of A* to optimize the path built by RRT for smoother traveling. The additional evidence of the model's efficiency to reduce travel time comes from the average time required to reach the target being reduced by about 50%, going from 40-50 seconds to 20-30 seconds. All of these results show how well RRT for exploration and A* for optimization combine to greatly improve in terms of energy efficiency, travel time, and path length.

5. Conclusion and Future Works

In this research, we successfully integrated the A* algorithm with Rapidly-exploring Random Trees (RRT) to design a robust and efficient path planning framework for autonomous vehicle navigation in IoT-enabled environments. This hybrid approach leverages RRT for real-time terrain exploration and A* for optimal path refinement, allowing autonomous systems to navigate dynamically changing and complex terrains with improved performance. Experimental evaluations demonstrated notable enhancements, including a 50% reduction in travel time, a 12–15% decrease in path length, and a 23% drop in energy consumption. These results confirm the framework's effectiveness in enhancing energy efficiency and real-time navigation, even under uncertain and obstacle-rich scenarios.Future research will focus on extending this hybrid framework by incorporating adaptive learning mechanisms using reinforcement learning or deep neural networks to enhance decision-making in highly unpredictable environments. Additionally, integrating richer environmental and sensory data, such as weather conditions, traffic density, and real-time vehicle-to-vehicle communication, can further improve path optimization and situational awareness. Scalability to multi-agent systems and urban-scale deployment with cloud-based coordination are also promising directions for expanding the practical applicability of this approach.

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