

Autonomous Drone Navigation Using Reinforcement Learning and Real-Time Sensor Data Fusion

M Shruthi¹, Dr Pradeepa D²

¹School of CSA, Reva University, Bengaluru, India

²Assistant Professor, School of CSA, Reva University, Bengaluru, India

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ABSTRACT

The increasing adoption of drones across domains such as surveillance, logistics, agriculture, and disaster response has intensified the need for reliable autonomous navigation systems. This work presents an adaptive navigation framework that integrates reinforcement learning (RL) with real-time multi-sensor data fusion. Unlike conventional rule-based approaches, the proposed method enables the unmanned aerial vehicle (UAV) to learn from continuous interaction with its environment. Data from GPS, IMU, LiDAR, and vision sensors are combined to construct a dynamic representation of the surroundings. Based on this representation, the RL agent incrementally improves its navigation strategy by evaluating past actions and outcomes. Experimental observations indicate improved adaptability, enhanced navigation accuracy, and more effective obstacle avoidance compared to traditional techniques.

Keywords—Autonomous drones; reinforcement learning; sensor fusion; UAV navigation; real-time systems

INTRODUCTION

The growing use of drones across fields such as security, delivery services, agriculture, and disaster response has created a strong need for reliable autonomous navigation. In many current systems, navigation depends either on manual control or predefined routes. While these approaches may work in controlled environments, they often struggle when conditions become uncertain or rapidly changing.

Reinforcement learning (RL), a branch of artificial intelligence, offers an alternative by enabling systems to learn through interaction rather than relying solely on fixed rules. Instead of following static instructions, an RL-based model continuously adjusts its behaviour by maximizing rewards associated with successful actions.

To address the limitations of conventional methods, this study explores an approach that combines RL with real-time sensor data fusion. By bringing together information from multiple sensors, the model forms a more consistent understanding of its surroundings. This enables better decision-making and supports navigation in environments where conditions cannot be predicted in advance.

To overcome the limitations of traditional navigation systems, this study proposes an adaptive drone navigation framework integrating reinforcement learning with real-time sensor data fusion. The proposed system offers optimal path planning, obstacle avoidance and autonomous decision-making. By utilizing learning-based techniques with multi-sensor integration, this study aims to enhance the accuracy of navigation, as well as provide the ability to adapt to changing environments, and therefore increase the reliability of the navigation system for use in real world applications

The purpose of this paper is to assist in the development of an intelligent drone navigation system combining reinforcement learning and sensor fusion. The intelligent drone navigation system enables the UAV to navigate in an efficient manner and adapt to changing environments

BACKGROUND

To navigate autonomously, drones depend on sophisticated sensors and computational methods [14] to detect and make sense of the world around them as they fly. A combination of onboard sensors (GPS, IMU, LiDAR, and camera) is utilized to build a complete representation of the UAV's surroundings. The output from each of these sensors is utilized to create either a spatial map or an environmental model, which is utilized to determine the optimal path for navigation, obstacle avoidance, and route planning

In the case of reinforcement learning, drones use data from sensors to define their environment as a decision-making process, usually defined using MDPs. The UAV is allowed to interact with its environment by receiving sensory input from it (i.e., the state of the world) and taking an action or decision based on what it has been taught about how to respond to the world at that moment. Accurate representation of state data is an important part of creating the UAV capabilities to accomplish its objectives and to effectively respond to changing conditions. The use of real-time sensor data fusion will enable the UAV to combine all of the different sensors [15] into one reliable and complete understanding of the surrounding environment

These systems are responsible for providing the UAV with accurate navigation as well as adapting the UAV to changes in the surrounding environment. However, there are various issues that may reduce the ability of these systems to operate effectively such as sensor error, delay in processing data, lack of consistency in the environment, and limited processing power

Finally, tracking and localization mechanisms are critical for providing real-time information on where the UAV is, how it is oriented in three-dimensional space, and how quickly it is moving

LITERATURE REVIEW

Standard path planning algorithms (e.g., A* and Dijkstra) that traditional navigation systems use operate effectively in static environments but lack the capacity to respond appropriately to dynamic and uncertain environmental elements. Reinforcement learning (RL) has recently emerged as a key approach [2], [3] as an important area of research in robotics and autonomous systems with respect to adaptive decision-making. There are still issues related to the ability to implement RL in real time, sensor noise, and computational complexity, as studies have confirmed in many cases

The recent use of RL in robotics and Unmanned Aerial Vehicle (UAV) navigation has increased. UAVs learn from their surroundings and adaptively modify their behaviour through time to perform better; for example, earlier versions of RL methods (e.g., Q-Learning) were limited to simple navigation tasks in small and simple navigation tasks (e.g., stationary environments)

In order to accommodate greater complexity and enable continued enhancements and more effective navigation via UAVs, more advanced methods of using RL (e.g., Deep Q Network [DQN] and Proximal Policy Optimization [PPO]) have also been introduced. DQN utilizes a deep learning architecture, allowing it to better deal with the complexities and challenges of decision-making environments and enhance decision-making speed and capability. The literature indicates that DQN is beneficial for avoiding obstacles while utilizing PPO enables more efficient and stable learning; however, DQN and PPO require more computational processing power and longer periods of training than other methods of utilizing RL

The research community has utilized sensor engine technology along with sensor-based techniques such as Kalman Filter for fusing sensor data from GPS, IMU, and LiDAR to provide more accurate locations for the UAV. By fusing these data types, the UAV will be more aware of its surroundings than if it just relied on one sensor alone. Both Reinforcement Learning (RL) and sensor fusion enhance adaptability and performance in

UAV navigation; however, there is still no adequate solution that offers an effective combination of both techniques for reliable autonomous real-time navigation

Table I Literature Review Comparison

SI No	Analysis			
	Paper Title	Author(s)	Key Contribution	Limitations
1	Q-Learning for Autonomous Navigation	Watkins et al	Introduced RL for basic navigation	Works only in simple environments
2	Deep Q-Network for UAV Control, 2015	Mnih et al	Applied deep RL for decision-making	High computational cost
3	PPO for Continuous Control, 2017	Schulman et al	Stable and efficient policy learning	Requires large training data
4	RL-based Path Planning for UAVs, 2019	Liu et al	Adaptive path planning using RL	Limited real-world testing
5	Autonomous Drone Navigation with DQN, 2020	Wang et al	Enhanced obstacle avoidance	Training instability
6	Vision-Based Drone Navigation, 2021	Zhang et al	Camera-based environment understanding	Sensitive to lighting conditions
7	Sensor Fusion using Kalman Filter	Welch et al	Enhanced localization accuracy	Sensitive to noise
8	Multi-Sensor Fusion for UAV Navigation, 2022	Chen et al	Combines GPS, IMU, LiDAR	Complex system integration
9	Deep RL for Obstacle Avoidance, 2020	Tai et al	Reduced collision rates	Slow convergence
10	RL-based Navigation in Dynamic Environments, 2021	Singh et al	Handles dynamic obstacles	Requires extensive training
11	UAV Navigation using Reinforcement Learning, 2022	Kumar et al	Efficient path optimization	Hardware dependency
12	LiDAR-Based Autonomous Navigation, 2021	Park et al	Accurate distance measurement	Expensive sensors
13	Vision + RL for Drone Control, 2022	Garcia et al	Combines vision with RL	High processing requirements
14	Sensor Fusion with EKF for UAV, 2020	Brown et al	Enhanced tracking accuracy	Computational overhead
15	RL-based Autonomous Flight System, 2023	Sharma et al	Enhanced real-time decision-making	Limited scalability
16	Deep Learning for Drone Navigation, 2022	Lee et al	High accuracy in complex environments	Needs large datasets
17	Autonomous UAV with Multi-Sensor Integration, 2023	Patel et al	Better environmental awareness	Integration complexity
18	RL with Real-Time Sensor Fusion, 2024	Verma et al	Combines RL with sensor fusion	Real-time challenges
19	UAV Navigation using PPO Algorithm, 2023	Reddy et al	Stable learning performance	Slow training process
20	Intelligent Drone Navigation System, 2024	Multiple Authors	End-to-end autonomous system	Early-stage research

A comparative analysis of recent studies is presented in Table I [4]–[20]. The analysis demonstrates that while existing methods enhance navigation and obstacle detection, they still face challenges in real-time adaptability, continuous learning, and efficient integration of reinforcement learning with sensor data fusion

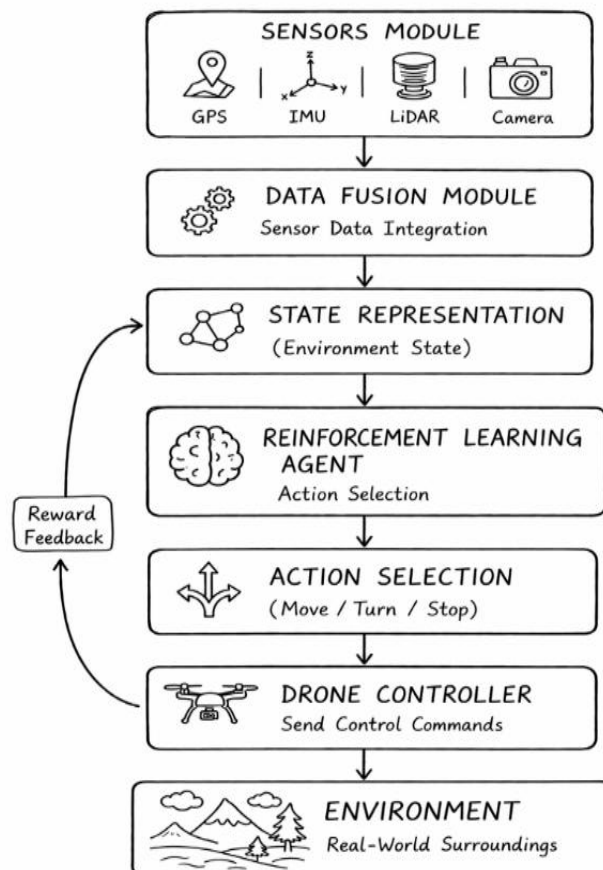
METHODOLOGY

The design of the new drone navigation system is based on both reinforcement learning and sensor fusion in order to allow an unmanned aerial vehicle (UAV) to make intelligent decisions when flying. The process is structured into multiple stages, including data acquisition, fusion, state representation, action selection, and iterative learning.

Data from sensors such as GPS, IMU, LiDAR, and cameras are first gathered simultaneously. Since each sensor provides a different type of information, combining them helps reduce uncertainty and improves reliability. The fused data is then organized into a structured format that represents the current state of the environment, including position, orientation, and nearby obstacles.

Based on this state, the learning agent evaluates possible actions and selects one that is likely to produce the best outcome. Over repeated interactions, the agent refines its behaviour using feedback in the form of rewards and penalties. This gradual improvement allows the model to adapt its navigation strategy as conditions change.

Fig. 1. Proposed system architecture



A. Sensor Module

The sensor module is the first of three components of the model. Sensors include GPS (global positioning system), IMU (inertial navigation system), LiDAR (light detection and ranging), and cameras that generate real-time feeds, all three in parallel to collect accurate data about a drone's position, speed, heading, and any objects around it. All collected data contributes to situational awareness of the immediate environment

B. Data Fusion Model

All sensor data is aggregated into one collection; because the data provided by each sensor is different, data fusion offers an enhanced level of accuracy and reliability [15] in our understanding of the environment. In addition, data fusion reduces the errors and noise caused by individual sensors when they are isolated

C. State Representation

The data has been combined into a structured representation known as a “State.” The state describes where the UAV currently is (location), how close it is to obstacles (distance from obstacles), and how it is oriented (direction). The learning models will then utilize this information to make decisions

D. Reinforcement Learning Agent

In this system, the RL agent is considered the primary function because it makes decisions based on its observations of the environment/state(s) of the moment. The RL agent assigns rewards to actions and applies penalties for incorrect actions, thereby learning from their past errors and ultimately improving their overall decision-making ability through experience and growth over time.

E. Action Selection

An algorithm designed by the RL agent enables comparison of alternative actions. The UAV was able to choose from a list of possible actions that included moving straight ahead, turning left, turning right, or stopping to avoid obstacles. Additional actions can be incorporated depending on mission requirements.

F. Drone Controller

The UAV controller executes the selected action. It sends control commands to the UAV motors and ensures that the movement is performed correctly

G. Environment

The environment represents the real-world surroundings in which the UAV operates. It includes obstacles, terrain, and other objects. The environment is continuously interacted with by the UAV while navigating

H. Reward Feedback

Once an action is taken, the model receives reward feedback. An example of positive reward would be when a drone completes a successful action (such as avoiding an obstacle) and reaches the final destination. Any time a drone fails (for example, touching or crashing into an object) while trying to achieve a goal, it will receive a penalty reward. The RL agent uses received rewards as information to increase its knowledge about how to better accomplish tasks in future attempts

RESULTS

The proposed navigation approach is evaluated against existing methods to understand its effectiveness. The combination of reinforcement learning and real-time sensor fusion shows noticeable improvements, particularly in environments where conditions are not static.

Because the model continuously learns from interaction, it is able to adjust its decisions when new obstacles or changes occur. At the same time, integrating data from multiple sensors improves the accuracy of environmental understanding, which helps reduce navigation errors.

Although the current evaluation is mainly based on simulation, the observed performance suggests that the approach has potential for real-world application. Further testing outside simulated environments will be necessary to confirm its reliability under practical conditions.

A. Expected System Performance

Table I [4]–[20]. By utilizing real-time sensor data and learning-based decision-making, the proposed system improves navigation accuracy for the UAV, allowing it to select optimal flight paths and avoid potential obstacles. This reduces error rates associated with UAV navigation [5], [6]

B. Real-Time Adaptability

Continuous feedback from the environment enables the model to adapt to changing conditions. The UAV can respond quickly to new obstacles and environmental changes during flight

C. Decision Support Efficiency

The reinforcement learning agent facilitates fast and efficient decision-making. It selects the best action based on the current state, improving overall navigation speed and performance

D. System Limitations

Since the model is primarily evaluated in simulation, real-world validation remains limited. Challenges such as sensor noise, hardware limitations, and computational requirements may affect performance in practical applications

Table II. Methodology Analysis

S No	Methodology Step	Description
1	Data Collection	Collect data from sensors such as GPS, IMU, LiDAR, and cameras during drone operation
2	Pre-processing	Clean and process sensor data to remove noise and enhance accuracy
3	Data Fusion	Combine data from multiple sensors to get a complete understanding of the environment
4	State Representation	Convert fused data into a structured format for the RL model
5	Reinforcement Learning	Train the RL agent to learn optimal navigation actions using rewards
6	Action Execution	Perform actions such as move, turn, or stop based on agent decision
7	Environment Interaction	Drone interacts with surroundings and collects feedback
8	Performance evaluation	Analyze navigation accuracy, collision rate, and path efficiency

FUTURE WORK

Incorporating cutting-edge AI techniques into the proposed drone navigation system improves its decision-making capabilities, assists in identifying obstacles, and enables optimization of routes. Using advanced deep learning algorithms improves speed and offers greater accuracy.

Developing new technologies for sensor types and fusing data together offers a better understanding of the environment, which in turn would enhance system performance capability to function within different environments. Advanced sensor technology combined with advanced simulations yields a more realistic and reliable system

Testing the model in real-world conditions enables verification of its functionality under a wide range of environmental conditions (e.g., weather, terrain). Conducting large-scale testing will provide an opportunity to determine the accuracy of navigation; the levels of safety; and how efficient the model may be

Future enhancements to the model could include working with multiple drones in a coordinated manner to perform tasks such as surveillance and delivery through the use of communications technologies such as 5G

Using a combination of cloud computing and edge computing could facilitate the collection and processing of large data sets in real time as well as provide greater scalability by allowing faster data processing and enhanced performance of the model.

Research that is done in the future should also look to make systems safer, more private, and more reliable when used. Methods such as reducing costs through better access could help ensure this technology becomes available to all types of consumers and businesses

CONCLUSION

This study presents a drone navigation approach that combines reinforcement learning with real-time sensor fusion to support adaptive decision-making. By moving away from rigid rule-based systems, the framework allows the UAV to adjust its behavior based on experience.

The results indicate improvements in navigation efficiency, reduced collision likelihood, and better overall performance in changing environments. As the model continues to learn, its ability to respond to complex situations also improves.

While the current work is primarily validated through simulation, it provides a foundation for further development. Future implementation in real-world scenarios could help refine the approach and expand its practical use in autonomous drone operations.

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