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Autonomous Trajectory Planning For Unmanned Aerial Vehicle

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***Abstract*—Unmanned aerial vehicles (UAVs) have a significant problem in autonomous navigation in new or unpredictable situations. To address this issue, the system produces a path between two points, and the drone is commanded to follow this path based on its location. In this study, we provide a novel framework for autonomous UAV route planning based on deep reinforcement learning. The goal is to approach moving or stationary targets using a self-trained drone (UAV) as a mobile aerial unit in a 3-D urban setting. UAVs, particularly rotary- wing aerial robots such as quadcopters, offer a high level of mobility, making them appropriate for a wide range of activities and applications. To provide a safe autonomous flight with limited mission time or battery life, the most efficient path must be determined. The quadrotor UAV in our trials continually monitors its position and battery level and modifies its course accordingly. We simulate the behaviour of autonomous UAVs in several conditions, including obstacle-free and urban environments. Our findings show that the UAV is capable of choosing clever paths to its objective.**

I. INTRODUCTION

UAVs can be remotely piloted by humans or capable of autonomous flight. They are often used by the military and police when it is too risky to send a human-piloted aircraft, or when it is impractical to use a manned aircraft. The International Civil Aviation Organization, or ICAO, refers to UAVs as unpiloted aerial vehicles or remotely piloted aircraft. UAVs have already revolutionized military and special operations, and their use is expanding to a variety of other applications. Commercial drones are smaller versions of consumer drones that are used for commercial purposes. Users typically control the speed and altitude settings when these drones take off. Delivery drones can withstand extreme temperatures and high winds, making them ideal for delivering packages quickly. Amazon is currently developing a drone delivery system that promises todeliver items within 30 minutes of payment. Commercial drones are also used for surveillance, including monitoring livestock, mapping wildfires, securing pipelines, and patrolling roads and homes. They are also useful for commercial and film production. Utilizing this technology can speed up services and improve efficiency in various industries.

II. BACKGROUND

Drones that are autonomous are unmanned air vehicles (UAVs) that do not require a human pilot and depend on navigation and operating software driven by Artificial Intelligence (AI). Originally developed for military missions that were too dangerous or uninteresting for humans, by the turn of the twenty-first century, UAVs had become essential assets for most militaries worldwide. As control technologies improved and costs decreased, the use of UAVs in non-military applications has increased, including emergency response by crew members in the field. Drones are categorized based on their altitude range, endurance, and weight, and they are utilized for a variety of objectives, including military and commercial uses. UAVs today perform a variety of tasks, including climate change monitoring, search and rescue operations during natural disasters, photography, videography, and package delivery. The military's most well-known and controversial use of drones is for reconnaissance, surveillance, and precision strikes.

III. LITERATURE SURVEY

This paper [1] presents a novel implementation of model-based reinforcement learning (RL) as a high-level control mechanism for self- navigation of unmanned aerial vehicles (UAVs) in unfamiliar or unpredictable settings with short battery life. The suggested technique was tested in a simulated environment using a quadrotor UAV, and the findings show that the system can learn an effective trajectory in a few iterations and perform actions in real time. The experiment also revealed that TEXPLORE, the model-based RL algorithm, significantly outperformed the Q-learning-based method. This is a promising step toward enhancing the autonomous behavior of UAVs, and it highlights the potential of RL frameworks in addressing the challenges faced by UAVs in autonomous navigation.

The Author of this paper [2] Path planning, localization, and control procedures are included in this strategy for autonomous drone delivery jobs. The recommended method evaluates quadrotor posture using computer vision algorithms and UWB sensors, and an enhanced Kalman filter allows a sensory combination with the DJI-SDK stance of the drone.. A vector field-based controller issues the orders that allow the drone to go from its launch site to its landing platform. The experimental results indicate that the suggested strategy is suitable for a full autonomous delivery operation, and that the proposed localization method outperforms the DJI-SDK posture estimation alone during landing attempts. In addition, the system is proven to be robust in the event that one of the localization strategies fails.

However, there are still obstacles to overcome, such as the need for GPS-capable environments devoid of obstructions and known and constant load mass. Future works will address these concerns, as well as mechanical design considerations and the adjustment of controller parameters for smooth flight and landing precision.

In this paper [3], The proposed framework for autonomous UAV navigation in urban environments is

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based on deep reinforcement learning using a DDPG algorithm with a continuous action space. The objective of the framework is to train the UAV to determine its trajectory to reach a designated target while avoiding obstacles. The framework employs a transfer learning strategy to maximise the reward function, which is designed to balance select direction and hurdle penalty. The simulation findings show that the Quadcopter may acquire knowledge how to maneuver in real-time and avoid collision with objects.

The proposed framework has potential applications in various areas, such as parcel delivery, search and rescue, and surveillance. However, there are still some challenges to overcome, such as the accuracy of the obstacle detection system, which can affect the performance of the UAV. Additionally, the proposed framework is currently limited to numerical simulations, and it needs to be validated in real-world scenarios to assess its effectiveness and robustness.

In conclusion, the proposed framework presents a promising approach to overcome the challenges of autonomous UAV navigation in urban environments. By using deep reinforcement learning, the UAV can learn to navigate in real-time and reach its goal while avoiding hurdles. The framework has potential applications in various areas and can be further improved by addressing the existing challenges.

In this paper [4], The construction of a general drone navigation system that can navigate the drone to the issue area using data from onboard sensors is discussed. This is especially significant in risky and safety-critical circumstances when issue identification must be swift and accurate. The technique presented in the study combines Policy optimisation at the proximal level Deep reinforcement learning is combined with progressive module development and neural networks with long- term, short-term memory to build an adaptive and autonomous system capable of decision-making. To show accuracy and efficacy, the study compares multiple system configurations to a heuristic technique. Finally, the paper discusses the importance of ensuring the safety of the drone in real- world scenarios, and evaluates the performance of the drone using the developed navigation algorithm. Overall, the paper presents a promising approach to the development of mobile robots that are adaptable and autonomous, with decision-making power, for use in monitoring and data collection in various environments.

In this paper [5], offers a new handover technique for a drone system with wireless connectivity. that use reinforcement learning to optimise handover decisions while also ensuring strong Support for communication over wireless networks and mobility for drone user equipment (UEs). The Q-learning method is used to optimise handover decisions for a particular flight trajectory in real time, and the reward function may be changed to balance the number of handovers with the received signal intensity.

While the simulation findings show considerable gains in minimising the frequency of handovers while maintaining stable connectivity, the study has several drawbacks that require more investigation in the future. To begin, the existing framework only addresses drone movement in two dimensions; the next natural step is to enable three-dimensional mobility of drones. Second, the testing region and flight routes explored in this work are extremely limited, and it would be interesting to see if the results are valid for wider trial regions and extended flight paths with a bigger possible cell pool. Finally, because the proposed framework and experiments are based on an indication of received signal intensity, (RSRP), future research may consider adding additional parameters to the model to improve its performance.

This paper [6] focuses on the creation of an autonomous drone navigation system for package delivery, with the major tools being GNSS and a compass. The primary purpose of the research is to give critical medical assistance for emergency situations and to integrate them in Indonesian agriculture, in accordance with Society 5.0's great mission and big data. To simplify autonomous navigation throughout the transmission process, the proposed navigation algorithm makes use of course- over-ground data. In the trial, the proposed method proved effective in allowing a drone to duplicate a package delivery operation with enough navigation and acceptable landing site variance. However, the data showed that the distances smaller than 1 m, guidance using the field-over-ground strategy is not any more effective than navigation using GNSS and compass.

The proposed system has several features, including altitude and speed settings, interactive sensors for item delivery, and a user-friendly mobile application interface. The system can operate independently from the Ground Station, enabling a drone and mobile application to perform a delivery mission. The navigational algorithm established in this study might have potential uses in other sectors, such as drone combat, and could be further refined and adapted to travel from any distance and for any purpose utilising more accurate and adaptable algorithms.

Overall, the research presented in this paper provides insights into the development of autonomous drone navigation systems for package delivery and highlights the potential applications of such systems in various fields.

Delivery via Autonomous Aerial Vehicles (UAVs) is thriving. In this paper [7], Deep reinforcement learning is used in a unique approach for autonomous navigation of UAVs in complicated, unfamiliar surroundings. The approach does not rely on course planning or map construction, instead relying on sensory data from the surrounding environment and GPS signals. The navigation problem is modelled as a partly observable Markov decision process (POMDP), and an actor-critic architecture-based quicker method for POMDP policy learning is developed. The suggested method's usefulness is evaluated by simulations in five virtual settings, and the findings show that it is successful in allowing UAVs to travel securely and effectively in complex, unfamiliar surroundings.

This paper [8] suggests an approach Based on the new details, I gather that the study provides a deep reinforcement learning-based solution for autonomous path planning for UAVs in situations with many obstacles. Based on the Twin Delayed Deep Deterministic Policy Gradients (TD3) algorithm, the proposed technique comprises a two- stream

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Actor-Critic network structure that captures environment attributes from both observations and changes in observations to account for environment randomness and dynamism. In terms of flexibility and generality, the method surpassed DDPG and regular TD3 in simulated settings. The proposed technique enables drone to navigate safely in dynamic and heterogenous environments, which is crucial in scenarios like search and rescue and surveillance.

In this paper, [9] The project aims to address the problem of a single unmanned aerial vehicle (UAV) performing integrated detection, mapping, and navigation in an unknown area. The UAV is furnished with a low-complexity radar for this purpose, and its trajectory is tailored to optimise mapping precision while avoiding places where data may not be relevant for target identification. The Markov decision process (MDP), with the drone operating as an agent that infers its own navigation strategy using Either a state estimator or a reinforcement learning (RL) approach is used for identifying targets and area mapping. The results of the numerical simulation validate the proposed method, emphasising the UAV's capacity to explore regions with a high likelihood of target detection while autonomously recreating the surrounding environment.. Overall, this paper provides a uniqueapproach to dealing with the difficulty of combining identification, the mapping, and navigational instruction for a single UAV, which might have important implications in sectors such as emergency response, monitoring and tracking the environment.

In this paper{10], A reactive controller based on neural networks enabling micro UAVs to manoeuvre independently in unexpected outside environments. Control signals are generated by the controller utilising current sensor data rather than optimisation or configuration space searches, which reduces processing requirements. To address the navigation problem, which is modelled as a Markov Decision Process, deep reinforcement learning is applied. In addition, the authors present model explanation approaches based on feature attribution to give both visual and textual explanations of flying decision- making results. Global assessments can also be performed by the trained neural network will be evaluated and improved by professionals. The outcomes of the simulation demonstrate that the suggested technique gives an adequate justification for the generated module, which is advantageous for both first-time users and controller architects. The real-world testing show that the reactive controller works. outperforms conventional approaches using the same computational resources.

Using a PID+ Q-learning algorithm, [11] This study describes a system for employing reinforcement learning to enable unmanned aerial vehicles (UAVs) to navigate in areas where an accurate mathematical model may not be accessible. To illustrate the effectiveness of the suggested strategy, the authors conducted both simulation and actual implementation trials. The technical elements of implying reinforcement learning algorithms to drone systems and UAV flight programs were also discussed, with the goal of furthering research in this subject for critical applications like as wildfire monitoring and search-and-rescue operations. The proposed method is able to deal with environmental uncertainties, such as wind and other environmental dynamics, and provides a simple and effective solution for training UAVs to navigate in unknown environments.

IV. Methodology

A simulation in the MATLAB environment to validate the RL-based navigation concept for a quadcopter. The quadcopter's mission is to navigatefrom the starting position to the target position in the most efficient manner possible, with the ability to adjust the linear/angular velocity. The simulation uses a motion capture system to provide the quadcopter's position relative to the environment. The system uses a PID controller to facilitate the quadcopter's action and examines the system's behavior in specific scenarios. The framework's effectiveness is visualized in terms of error rate and task completion. The experiment is designed to illustrate a quadcopter whose mission is to find the most efficient route to the destination while monitoring its battery level and making intelligent decisions, such as rerouting for battery recharging at intermediate intervals. The quadcopter is viewed as a rigid body to which torques and forces are applied by four square-shaped rotors. The simulation uses a predetermined path in trajectory mapping, and the quadcopter is programmed to follow the calibrated trajectory to reach its destination.

V. Result

After building a model, it is very important to know the mapping ability of the model for new instances. You might want to try different paths with the model for the same Trajectory map, and then simply compare them in terms of performance. The shortest path must be selected and the time taken for the drone to reach the destination should be minimum also the endurance of the UAV must be considered during the real-time testing. This model implements a set of position states precisely by location, heading, turn curvature, and turn direction to generate a trajectory consisting of a collection of waypoints. The predefined data contains poses for specific locations where the toy quadcopter utilizes its cameras, allowing the pilot on the ground to estimate the altitude of the snow on the roof. Each of the supplementary power generators has three no-fly zones so that, in the event of a quadcopter malfunction, it does not cause damage to campus infrastructure. The red line represents the flight path, while the black x-markers indicate a change in trajectory or a particular pose. Poses are accompanied by blue lines that indicate the direction to a particular waypoint. Green circles indicate no-fly zones. The next part, Importing the mamo model UAV for the implementation of the proposed model to simulate in the defined Path.

The overall performance of the drone simulation was successful, The pre-planned Trajectory helped the drone to follow the given route and make travel from the source to the destination point with a minimal amount of time. The trajectory calibration is the difficult part of this project as it has to consider many obstacles and environmentalcongestion for any accidents or loss of control of the drone. Even though this project was done in a virtual

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environment it has to follow a certain path and No- Fly zone area to be avoided collision with a building or an object that is created in 3D Modelling.

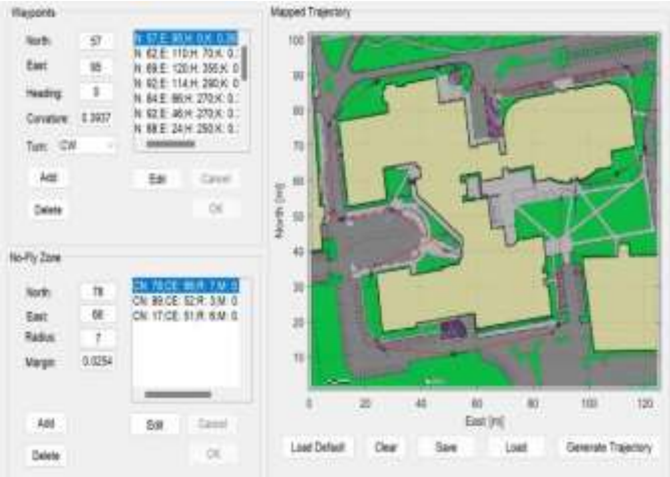

Fig. 1

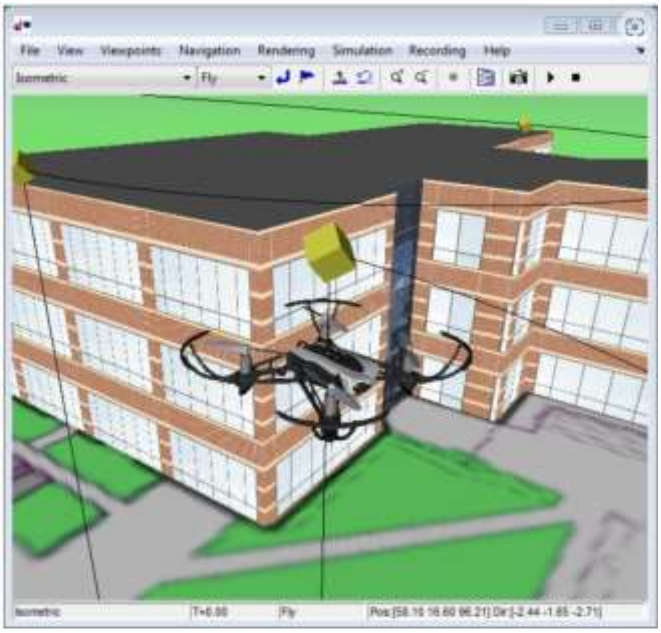

Fig: 2

FUTURE ENHANCEMENTS

Future research will concentrate on conducting experiments with quadcopter UAVs equipped with Reinforcement Learning and Obstacle avoidance and will investigate the difficulties of operating in the continuous domain. We also intend to achieve improvements in path planning, taking into account obstacle avoidance and power efficiency. Implementing reward-based reinforcement learning canimprove the capability of path planning, and the use of YOLO or SSD can improve obstacle avoidance by combining a camera and sensors to have both visual and sensory types of assistance for preventing accidents or damage to the unmanned aerial vehicles.

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