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Unmanned Aerial Vehicle (UAV) "Drones" using Machine Learning

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ABSTRACT

Unmanned aerial vehicle decision-making issues are increasingly being addressed using reinforcement learning (RL) (UAVs). The current advances in RL-based algorithms for UAV applications, encompassing both single-agent and swarm scenarios, are thoroughly reviewed in this work. First, the basic concepts of RL and its variants are introduced, followed by an overview of the state-of-the art RL algorithms that have been applied to UAV navigation, path planning, and obstacle avoidance. The study then examines real-time learning concerns, model selection, and exploration-exploitation trade-offs, as well as challenges and potential for employing RL in UAV systems. In order to further the use of RL in UAVs, future research initiatives are also suggested. They include creating hybrid methods that integrate RL with other methodologies and incorporating human feedback and domain expertise into the learning process. Overall, this work demonstrates the potential of this approach to improve the autonomy, adaptability, and resilience of UAV systems and serves as a significant resource for researchers and those interested in applying RL to UAVs.

Keywords— UAV, Autonomy, Reinforcement, Aircraft Vehicle

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), also known as drones, are aircraft that operate without a human pilot on board. They are controlled remotely or can fly autonomously using onboard computers and sensors. UAVs come in various shapes and sizes, from small consumer drones to large military drones. The field of unmanned aerial vehicles (UAVs) has seen a lot of progress and innovation in recent years, including the past three. There have been significant advances in areas such as flight performance, sensor technology, safety and reliability, autonomous flight, and specific applications. Unmanned aerial vehicles (UAV), also referred to as ”drones,” are small aircraft that are capable of flight using air currents and other driving forces, autonomous flight, the ability to carry payloads, and remote control operation. In many nations around the world, the ageing population and lengthening lifespans constitute a significant challenge for healthcare services and systems.

The two primary options—personal care at home or in a nursing home—require a lot of labour and cost a lot of money for the elderly, their families, and the healthcare system. Current developments in computing, networking, and sensor technologies have made it possible to treat these problems effectively and affordably while extending the independent lives of the elderly. The use of photography from unmanned aerial vehicles (UAVs) is expanding rapidly right now. In fact, data acquired from a bird's-eye perspective is especially pertinent for a wide range of applications, from agricultural to monitoring services. Tele surgical robots has the potential to enhance medical operations when unmanned extraction vehicles become a reality in the war arena. This project showcased an experimental surgical robot that used a network architecture made out of unmanned aerial vehicles (UAVs). During the COVID-19 crisis, when there were broad, widespread epidemics of contagious diseases, drones and UAVs were crucial in giving humanitarian supplies. This infectious disease has an impact on everyone in the world, and every instrument at our disposal has been employed to combat it. This technique has the potential to provide medical supplies in remote locations or during calamities. Delivery to islands without access to land transportation is challenging, and after a disaster, there is a higher danger of adverse conditions (such as delivery over terrain where bridges have failed or across rivers that have flooded). Drones, also referred to as unmanned aerial vehicles, are one such technology. They have been crucial for many military applications for a long time, but more recently, they have also asserted themselves in our daily lives. Drones have quickly emerged as the next disruptive force in our culture, disrupting everything from weather monitoring and gaming to photography and transportation.

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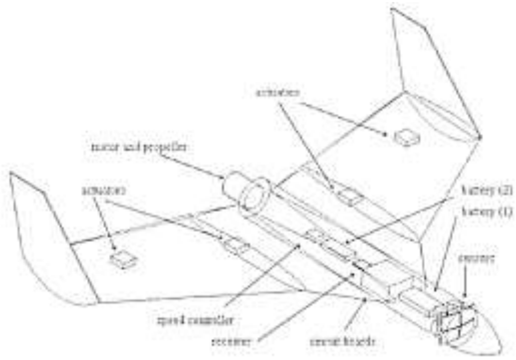

Figure 1: Basic element of an uav

These Unmanned Aerial Vehicles (UAVs) have become increasingly popular in various applications such as military, civilian, and commercial sectors due to their unique capabilities and advantages. However, the effective operation of UAVs in complex and dynamic environments is still a challenging task. One of the approaches to tackle this challenge is the application of Reinforcement Learning (RL) techniques in UAVs. This paper aims at providing a review of the most relevant, cutting-edge research on applying RL algorithms to UAVs. It also attempts to address the potential advantages and difficulties related to the application of RL in UAVs. Additionally, this study analyses current advancements and trends in RL-based UAV applications and identifies potential future research topics.

II. UNMANNED AERIAL VEHICLE-FUNDAMENTAL AND CLASSIFICATION

A. Fundamental of an UAV

Unmanned Aerial Vehicles (UAVs) are aircraft that are operated without a pilot onboard. They are also known as drones, and they come in a wide range of shapes and sizes, from small quadcopters to large fixed-wing aircraft. Here are some of the fundamental components and features of a typical UAV is shown in figure [1]

- Power Source: UAVs require a power source to operate, usually in the form of a battery or fuel cell. The power source is typically located on the body of the UAV and provides energy to the motor(s) that drive the propellers or rotors
- Flight Control System: UAVs are equipped with a flight control system that includes sensors, actuators, and a flight controller. The flight control system is responsible for stabilizing the UAV in flight and controlling its movement in three dimensions. The flight controller processes data from the sensors and provides commands to the actuators to adjust the UAV's attitude and speed.
- Communication System: UAVs need to communicate with a ground station or other devices to receive commands, transmit data, and receive updates on their status. This is typically done using wireless communication technologies, such as radio or satellite links.
- Payload: UAVs can carry various types of payload, such as cameras, sensors, or other equipment, depending on their intended application. The payload is typically mounted on the body or undercarriage of the UAV and is controlled by the onboard flight controller.
- Navigation System: UAVs need a navigation system to determine their position, orientation, and velocity. This can be done using Global Navigation Satellite Systems (GNSS) such as GPS, as well as inertial sensors and other techniques.

These are some of the fundamental components of a UAV. However, there are many other factors that can influence the design and capabilities of a UAV, such as its size, range, endurance, and payload.

B. UAVs Taxonomy

Unmanned Aerial Vehicles (UAVs) can be categorized into various types based on their size, shape, weight, capabilities, and applications. The UAV taxonomy can be classified into several categories, including:

1. Fixed-wing UAVs: These UAVs are designed with a fixed-wing structure, similar to a traditional aircraft. They have a longer range and can fly for a more extended period without requiring frequent battery recharges.

2. Rotary-wing UAVs: Also known as multirotor UAVs, these drones have multiple rotors and are designed for vertical takeoff and landing (VTOL). They can hover in place and are useful for applications that require precise positioning.

3. Hybrid UAVs: These drones combine the features of fixed-wing and rotary-wing UAVs, making them suitable for applications that require both long-range flight and vertical takeoff and landing capabilities.

4. Nano UAVs: These are small UAVs typically weighing less than 100 grams and have a limited range and flight time. They are suitable for indoor applications and close-range surveillance.

5. Small UAVs: These UAVs typically weigh between 0.5 kg to 25 kg and are suitable for small-scale mapping, surveillance, and inspection applications.

6. Medium UAVs: These drones weigh between 25 kg to 150 kg and are suitable for applications such as aerial mapping, agriculture, and infrastructure inspection.

7. Large UAVs: These are heavy drones typically weighing more than 150 kg and have a longer range and flight time. They are suitable for applications such as cargo delivery, military surveillance, and search and rescue operations.

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The taxonomy of UAVs is constantly evolving as technology advances and new applications emerge. Different UAV types have specific strengths and limitations, and their selection depends on the requirements of the particular application

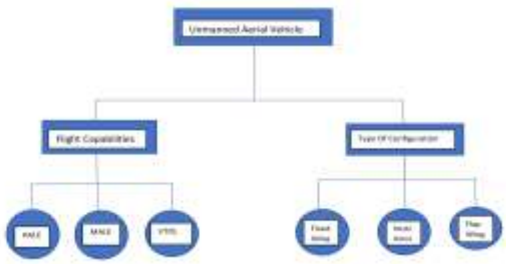

Figure 2: Unmanned aerial vehicle categorization

UAVs can be grouped according to their construction or according to how well they can fly. In Figure. 2, the classification is displayed. There are three primary types of UAVs, referred to as HALE, MALE, and VTOL, depending on their ability to fly. HALE (high altitude long endurance) can fly over 9000 m and has long flight endurance whereas MALE (medium altitude long endurance) can fly up to 9000 m. The capacity to take off and land vertically is a feature of VTOL (vertical take-off and landing). In addition, VTOL can transition to horizontal flight by the action of the propeller after ascending to a predetermined height above sea level [13].

III. REINFORCEMENT LEARNING

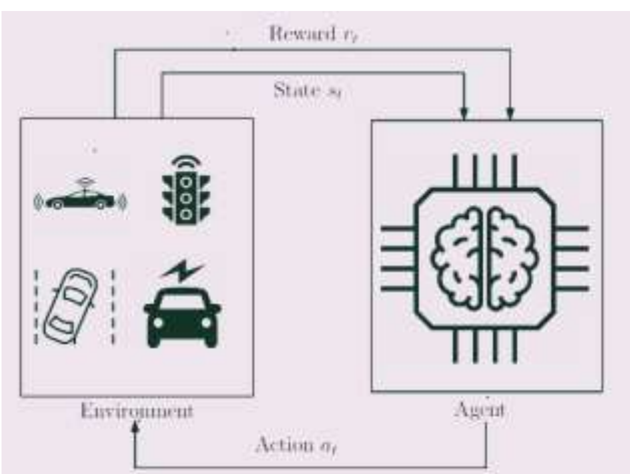

Figure 3: Reinforcement Learning Control Loop

RL is a type of machine learning that involves an agent interacting with an environment to learn through trial and error by maximizing a reward signal. By enabling UAVs to learn from their experiences and adjust to new environments, RL in UAVs aims to improve their performance. The application of RL algorithms in UAVs enables them to accomplish complicated tasks with more precision and efficiency by allowing them to make decisions based on their observations and actions in the environment. A type of machine learning called reinforcement learning (RL) enables an agent to pick up knowledge from its surroundings by getting feedback in the form of rewards or penalties. Reinforcement learning can be used to create autonomous control systems for unmanned aerial vehicles (UAVs) that allow them to carry out tasks like navigation, exploration, and surveillance. The basic goal of reinforcement learning is to identify an optimal policy, or set of guidelines, for the agent to use while making decisions. As the agent interacts with its environment and experiences rewards or penalties as a result of its behaviors, it gradually learns the policy through trial and error. [6] In a general RL model, an agent controlled with an algorithm, observes the system state st at each time step t and receives a reward rt from its environment/system after taking the action at. After taking an action based on the current policy Pi, the system transitions to the next state st+1. After every interaction, RL agent updates its knowledge about the environment. Figure 3 [5] depicts the schematic of the RL process. Reinforcement learning can be applied to UAVs to create autonomous control systems that allow the UAV to manoeuvre through challenging settings, avoid obstacles, and carry out particular missions. For instance, a UAV might be taught to fly over a predetermined region and take images of particular things or places without running into other things or other aircraft. Swarm intelligence algorithms, which allow a collection of UAVs to collaborate and carry out complicated tasks like coordinating search and rescue operations or mapping broad areas, can also be created using reinforcement learning. Overall, reinforcement learning has the potential to allow UAVs to function effectively and autonomously in a variety of conditions, making them attractive tools for a variety of applications. [15]

There are three main types of RL algorithms: value-based, policy-based, and actor-critic methods. Value-based methods learn a value function that estimates the expected reward of being in a given state or taking a particular action. 6 Policy-based methods learn a policy directly that maps states to actions. Actor critic methods combine both value-based and policy-based methods, where the policy is learned by an actor network, and the value function is learned by a critic network. One popular RL algorithm is the deep Q-network (DQN), which is a value-based RL algorithm that combines Q-learning with deep neural networks to enable learning from high-

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dimensional input spaces. DQN has been successfully applied to various domains, including Atari games and robotic control tasks. [9]

RL algorithms come in a variety of forms, including:

• **Value-based algorithms:** These algorithms learn a value function that estimates the expected cumulative reward for each state or state-action pair. Examples include Q-learning and SARSA.

• **Policy-based algorithms:** These algorithms learn a policy directly, without estimating value functions. Examples include REINFORCE and policy gradient methods.

• **Model-based algorithms:** These algorithms learn a model of the environment, which can be used to simulate future states and rewards. Examples include Dyna-Q and Monte Carlo tree search.

• **Actor-critic algorithms:** These algorithms combine elements of both value-based and policy-based methods by using two separate networks, one to estimate values and one to determine actions. Examples include A2C and A3C. [17]

IV. APPLICABILITY OF REINFORCEMENT LEARNING IN VARIOUS DISCIPLINES

In Agriculture: Reinforcement learning (RL) is a type of machine learning that involves training an agent to make decisions based on maximizing a reward signal. RL has a variety of potential applications in agriculture, from optimizing crop yields to reducing the use of harmful chemicals.

• Crop yield optimization: RL has been used to optimize crop yield by learning to make decisions about irrigation, fertilization, and other factors. In one study, RL was used to optimize the yield of a tomato crop by controlling the irrigation system [1]. The RL agent was able to achieve a 30 percent improvement in yield compared to a rule-based system.

• Pest control: RL has been used to develop strategies for controlling pests in crops. In one study, RL was used to optimize the use of pheromone traps for controlling the tomato leafminer pest [2]. The RL agent was able to reduce the number of traps needed by 35 percent, while maintaining the same level of pest control.

• Precision agriculture: RL has been used to develop strategies for optimizing the use of resources in precision agriculture. In one study, RL was used to optimize the use of nitrogen fertilizer in a wheat crop [10]. The RL agent was able to reduce the use of fertilizer by 50 percent, while maintaining the same level of yield.

• Livestock management: RL has been used to optimize the management of livestock by learning to make decisions about feed, water, and other factors. In one study, RL was used to optimize the feed intake of dairy cows [3]. The RL agent was able to reduce the amount of feed needed by 12 percent, while maintaining the same level of milk production.

In Transportation: Reinforcement learning has been used in transportation to improve the efficiency and safety of various transportation systems, such as autonomous vehicles, traffic signal control, and route planning.

• Reinforcement learning in transportation is the use of deep reinforcement learning for traffic signal control. The study demonstrates that the proposed method outperforms traditional traffic signal control methods and achieves better traffic flow efficiency. [4]

• Use of reinforcement learning for route planning in autonomous vehicles. a multi-agent reinforcement learning approach for robust route planning in autonomous driving [19]. The proposed method considers uncertainties in traffic flow and other external factors and achieves better performance compared to traditional route planning methods. Overall, reinforcement learning has the potential to revolutionize transportation systems by improving efficiency, reducing traffic congestion, and enhancing safety.

In Surveillance: Reinforcement learning has been applied to the field of surveillance to improve the efficiency and effectiveness of surveillance systems.

• Application of reinforcement learning in surveillance is the use of deep reinforcement learning for object tracking. [11] explores the use of deep reinforcement learning to track objects in surveillance videos. The study demonstrates that the proposed method achieves better performance than traditional object tracking methods and is more robust to object occlusion and other challenges.

• reinforcement learning for anomaly detection in surveillance videos. A method for anomaly detection in surveillance videos using deep video frame prediction and reinforcement learning [7]. The proposed method considers temporal and spatial information in the surveillance video and achieves better performance compared to traditional anomaly detection methods. Overall, reinforcement learning has the potential to improve the accuracy and efficiency of surveillance systems by enabling automated detection and tracking of objects of interest and anomalies in surveillance videos.

V. LITERATURE REVIEW

”The proposed approach offers a promising solution for addressing the challenges associated with UAV navigation and control in GPS-denied environments using Reinforcement Algorithm.”

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S. No	Name	Year	Finding	Algorithm Used	Limitation	Accuracy
1.	L. Cui	2022	Improved trajectory planning	DDPG	Limited exploration in high-dimensional action space	85
2.	Woonghee Lee	2022	The proposed system constructs the more reliable and robust SI (Swarm Intelligence) for UAV systems	federated reinforcement learning-(FRL	Limited to indoor environment	80
3.	Kong et al.	2021	Reinforcement learning can be used for adaptive UAV control in a dynamic environment	Deep Reinforcement Learning	N/A	N/A
4.	Liangliang and Lu	2021	Navigated a swarm of UAVs in a dynamic environment using collaborative multi-agent reinforcement learning.	Multi-Agent Deep Deterministic Policy Gradient (MADDPG)	Assumes perfect communication and sensing capabilities and does not consider communication failures or network delays.	Better formation maintenance and obstacle avoidance than the baseline approach
5.	Ahmed H. Tewfik et al.	2021	Reinforcement learning is a promising approach for UAV path planning and obstacle avoidance	Q-learning	N/A	N/A
6.	Jin-Woo Lee	2021	Local Dynamic Map Generation for Safe UAV Navigation	Local Dynamic Map (LDM) Generation Algorithm	limited real world testing	N/A
7.	Akash Singhania	2021	Developed an RL-based approach for UAV path planning	Actor-critic	Assumes that the UAV's sensors are perfect	N/A
8.	Benjamin Noack	2020	Developed an RL-based approach for UAVs to navigate in a city	Deep Q network	Assumes that the UAV's sensors are perfect	90
9.	Shang, Chao	2020	Multi-UAV autonomous cooperative transportation using deep reinforcement learning	Multi-Agent Deep Deterministic Policy Gradient (MADDPG)	Limited real world testing	High
10.	Chen, Liang	2020	Autonomous flight control for UAVs using deep reinforcement learning	Deep Q Network (DQN)	Limited real world testing	High
11.	Xiang Li	2020	Used RL to develop a system for UAVs to navigate in a city	Proximal policy optimization	Assumes that the UAV's sensors are perfect	90
12.	Kong, Xi-angwei	2019	Distributed multi-UAV path planning using deep reinforcement learning	Multi-Agent Deep Deterministic Pol icy Gradient (MADDPG)	High computational complexity	High
13.	Liu, Hong	2019	Real-time obstacle avoidance for UAVs using deep reinforcement learning	Deep Q Network (DQN)	Limited testing in dynamic environments	High
14.	Saad, Mohamad	2019	Cooperative path planning of multiple UAVs using deep R-learning	Multi-Agent Deep Deterministic Policy Gradient (MADDPG)	Limited to a fixed number of UAVs	High
15.	Loianno, Giuseppe	2018	GPS-denied indoor flight control for UAVs using deep reinforcement learning	Deep Deterministic Pol icy Gradient (DDPG)	Limited to indoor environments	High
16.	Fan et al.	2018	Deep reinforcement learning can be used to enable autonomous UAVs to fly through cluttered environments	Deep Q-Network (DQN)	N/A	85.3
17.	Wang et al.	2018	Coordinated multiple UAVs in a search and localization task using deep reinforcement learning.	Deep Q-Network (DQN)	Relying on a centralized communication network for coordination may not be practical in real-world scenarios.	Better search efficiency and localization accuracy than the baseline approach.

VI. REINFORCEMENT LEARNING'S LIMITATIONS IN UAVS

Reinforcement learning (RL) is a popular machine learning technique used for training agents to make decisions based on rewards and punishments received in response to their actions. RL has been used in the field of unmanned aerial vehicles (UAVs) for tasks such as autonomous navigation, target tracking, and search and rescue operations. However, RL also has some limitations when it comes to UAVs:

1. Sample Efficiency: RL requires a lot of data to learn a task, which can be time-consuming and expensive for UAVs as they are often limited by battery life and flight time.

2. Safety: UAVs operate in complex environments where safety is a critical concern. RL may not always guarantee safe operation, and it may take a long time for an RL agent to learn safe behavior in uncertain and unpredictable environments.

3. Generalization: RL agents are often trained on a specific task and may not generalize well to new environments or situations. In the case of UAVs, this means that an RL agent trained in one environment may not perform well in a different environment or scenario.

4. Exploration vs. Exploitation tradeoff: RL agents need to balance exploration (trying new actions to gather information) and exploitation (using the actions that have worked in the past) to maximize the reward. In the case of UAVs, exploration can be risky and can lead to crashes or other safety issues.

5. Limited interpretability: The decisions made by RL agents are often difficult to interpret, which can be problematic for UAVs where human operators need to understand the reasoning behind an agent's actions.

Overall, while RL has shown promising results in the field of UAVs, it is important to be aware of its limitations [14] and to use it in combination with other techniques to ensure safe and effective operation.

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VII. CHALLENGES OF REINFORCEMENT LEARNING IN UAVS

Reinforcement learning (RL) is a popular technique used for training autonomous agents to perform complex tasks. However, applying RL to unmanned aerial vehicles (UAVs) comes with several challenges, including:

1. Limited Flight Time: UAVs have limited battery life and flight time, making it challenging to collect enough data to train an RL agent.

2. Safety: UAVs operate in complex and dynamic environments, and safety is a critical concern. RL agents may not always learn safe behavior, and it can be time-consuming and expensive to ensure that an RL agent has learned to operate safely.

3. Real-time Decision Making: UAVs need to make decisions in real-time based on changing environmental conditions. RL algorithms can be computationally expensive, making it challenging to train and deploy an RL agent in real-time.

4. Generalization: RL agents can struggle to generalize to new environments or scenarios. In the case of UAVs, this means that an RL agent trained in one environment may not perform well in a different environment or scenario.

5. Data Efficiency: RL requires a significant amount of data to learn a task. However, collecting data from UAVs can be challenging due to limited flight time and the high cost of equipment.

6. Interpretability: RL agents can be difficult to interpret, which can be problematic for UAVs where human operators need to understand the reasoning behind an agent's actions.

7. Multi-agent Coordination: UAVs often operate in teams, and RL algorithms must learn how to coordinate the actions of multiple agents to achieve a common goal. Overall, while RL holds great promise for UAVs, addressing these challenges [16]is critical to ensure safe and effective operation. Researchers are actively working to develop new techniques and algorithms that can overcome these challenges and enable the widespread use of RL in UAVs.

VIII. CONCLUSION

In conclusion, this review paper has explored the recent developments and applications of unmanned aerial vehicles (UAVs) in reinforcement learning. The study has demonstrated that the combination of UAVs and reinforcement learning has shown promising results in various fields, including surveillance, agriculture, transportation, and search and rescue operations. The review has identified various reinforcement learning algorithms used for UAV control, including Q-learning, deep reinforcement learning, and policy gradient methods. Additionally, the review has highlighted the challenges associated with the application of reinforcement learning in UAVs, such as the high-dimensional action and state space, data efficiency, and safety concerns. Overall, the research on UAVs in reinforcement learning is still in its early stages, and further research is required to overcome the challenges and to extend the current applications. However, the potential of UAVs in combination with reinforcement learning is enormous, and it is expected that it will have a significant impact on the future of various industries. The findings of this review paper provide insights for researchers to identify research gaps, potential applications, and to develop effective algorithms for the control of UAVs using reinforcement learning.

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