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Deep Reinforcement Learning for Autonomous Drone Navigation: A Review

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ABTSTRACT

This study examines the growing importance of Deep Reinforcement Learning (DRL) as a transformative approach for autonomous UAV navigation in complex, dynamic, and uncertain environments. Traditional rule-based and model-driven control strategies struggle with real-time adaptation, high-dimensional sensory data, and unpredictable obstacles, highlighting the need for learning-based methods. DRL overcomes these limitations by integrating deep neural networks with reinforcement learning to enable drones to learn navigation policies directly from raw sensory inputs such as images, lidar, and depth data. The reviewed literature demonstrates significant advancements, including hybrid learning frameworks, improved state representations, dynamic reward designs, sensor-fusion architectures, and distributed DRL models that enhance stability, decision accuracy, and collision avoidance. Despite challenges such as high training cost, sim-to-real transfer gaps, and sensitivity to reward design, DRL continues to evolve as a critical technology for reliable, adaptive, and scalable UAV autonomy across diverse real-world scenarios.

Keywords: Deep Reinforcement Learning, UAV Navigation, Autonomous Systems, Sensor Fusion, Obstacle Avoidance

1. Introduction

Unmanned aerial vehicles (uavs) may now function with ever-higher degrees of intelligence, flexibility, and autonomy in a variety of application areas because to the quick development of robotics, autonomous systems, and artificial intelligence. Once limited to military reconnaissance and simple remote-controlled operations, drones are now essential tools in a variety of commercial, industrial, and scientific settings, including delivery systems, infrastructure inspection, precision agriculture, aerial imaging, environmental surveillance, disaster response, and precision agriculture.[1] However, the need for advanced navigation skills that go beyond the constraints of conventional rule-based, model-based, and manually adjusted control approaches has increased dramatically as UAV use spreads into complex, unexpected, and very dynamic real-world situations. Pre-programmed rules, manually created features, static path-planning algorithms, and traditional control methods like PID controllers, extended Kalman filters, and linear-quadratic regulators are all major components of conventional navigation systems. Even while these methods work well in controlled settings, they often have trouble with uncertainties in real time, generalizing to unknown situations, reacting to high-dimensional sensory inputs, or adjusting to changing impediments.[2] These limitations emphasize the need for computationally intelligent systems that can directly learn the best course of action via experience, introspection, and interaction with the environment—a capability that Reinforcement Learning (RL) essentially provides. An autonomous agent may learn to carry out tasks by obtaining rewards or penalties depending on its actions according to a mathematical framework called reinforcement learning, which allows it to find the best navigation strategies via trial-and-error learning.[3] However, the vast state-action space, the intricacy of high-dimensional sensor data (such lidar, camera pictures, and IMU signals), and the need for quick policy choices in real-time make traditional RL alone unsuitable for drone navigation. In order to overcome these difficulties, RL and Deep Learning (DL) have been combined to create Deep Reinforcement Learning (DRL), which allows uavs to process unprocessed sensory data using strong neural network architectures and acquire sophisticated navigational behaviors that are resilient, scalable, and condition-adaptable.[4]

Because it blends the representational capacity of deep neural networks with the decision-making prowess of reinforcement learning, deep reinforcement learning has become a potent paradigm for autonomous drone navigation. Without the need for explicit modeling of aerodynamics, environmental dynamics, or state-transition probabilities, DRL enables drones to learn navigation trajectories, obstacle avoidance tactics, collision-free motion planning, and control policies straight from images, depth maps, or environmental interactions.[5] Drones can now autonomously explore unknown environments, handle dynamic obstacles, adapt to uncertain wind conditions, and navigate cluttered indoor and outdoor spaces thanks to algorithms like Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), Proximal Policy Optimization (PPO), Twin Delayed DDPG (TD3), Asynchronous Advantage Actor–Critic (A3C), and Soft Actor–Critic (SAC).[6] These developments have expanded the capabilities of uavs, turning them into intelligent agents that can make choices in real time based on intricate sensor observations. DRL-based navigation is especially useful in GPS-denied situations like woods, tunnels, disaster zones, and urban canyons where traditional navigation systems fail since it does away with the requirement for human feature extraction and rule-based mapping. Additionally, by repeatedly running simulation episodes, DRL systems may learn and perform better over time, allowing for effective policy optimization without running the risk of causing physical harm to the drone in the early training phases. Because they provide safe and scalable settings to test a broad range of scenarios, weather conditions, obstacle configurations, and sensory noise profiles, simulation systems like Gazebo, airsim, ROS-based environments, and Unity3D have become indispensable for training DRL agents. Using methods like domain randomization, sim-to-real transfer learning, and sensor calibration algorithms, these rules may be applied to real-world drones after being learned in simulation, closing the gap between virtual training and actual deployment.[7]

DRL's importance for autonomous drone navigation stems from its capacity to allow uavs to function dependably in settings with non-linear dynamic interactions, unknown risks, and insufficient information. DRL enables drones to make choices based on partial observations and adapt to changing settings without previous information, in contrast to classic planning algorithms like A*, RRT, or Dijkstra, which depend on predetermined maps, deterministic rules, or completely observable environments.[8] In situations like search and rescue missions, when drones must maneuver through fallen structures, thick woods, or areas covered in debris with poor vision, this skill is crucial. Additionally, DRL enables uavs to operate together in multi-agent settings, advancing distributed sensing, formation control, coordinated surveillance networks, and cooperative drone swarms. Fields including environmental monitoring, agricultural field mapping, and large-scale disaster relief, where coordinated activities may greatly increase efficiency, accuracy, and coverage, might be revolutionized by these swarm-based DRL systems. By integrating DRL with sophisticated sensor fusion techniques, such as combining RGB cameras, stereo vision, lidar, ultrasonic sensors, and GPS/IMU modules, uavs' situational awareness is further improved, allowing them to navigate independently with high accuracy even in cluttered or visually difficult environments. To guarantee long-term operating dependability, DRL frameworks may also include safety restrictions, energy optimization guidelines, and flight stability procedures.[9] These can help with crucial problems including battery limits, wind disruptions, communication lags, and computing limitations.

Notwithstanding its revolutionary promise, DRL-driven autonomous drone navigation has a number of issues that need further research. In order to achieve steady convergence, training DRL agents requires a large quantity of data and is computationally demanding. Real-world exploration is expensive and risky due to the stringent safety and physical limitations that drones operate under, including limited battery life, dynamic aerodynamics, lag in sensor response, and collision risk. Furthermore, DRL algorithms are often sensitive to reward function design and hyperparameters, which may result in unstable learning or less-than-ideal policies if they are improperly constructed. Research is also being done to make sure that DRL policies are resilient to environmental uncertainties, sensor noise, and adversarial assaults. The "sim-to-real gap" is another significant problem, wherein policies that function well in simulations often deteriorate when implemented in real-world settings because of variations in lighting, texturing, wind, and sensor errors.[10] Enhancements in curricular learning, imitation learning, transfer learning, meta-learning, and hybrid DRL architectures that blend model-based and model-free techniques are necessary to meet these problems. Furthermore, the development of dependable real-time autonomous navigation may be accelerated by combining DRL with cutting-edge technologies including 5G/6G connectivity, edge computing, computer vision transformers, multi-sensor fusion, and quantum-enhanced optimization.[11]

Deep Reinforcement Learning presents a viable and potent way to enable autonomous drone navigation in dynamic and complicated situations.[12] It is a crucial technology for the next generation of intelligent UAV systems because of its capacity to learn from unprocessed sensory input, adjust to uncertainties in real time, generalize across settings, and constantly improve through experience. Strong DRL-based navigation frameworks are essential for improving safety, accuracy, efficiency, and autonomy as industries depend more and more on autonomous aerial systems for mission-critical operations.[13] Therefore, to advance the field and facilitate the deployment of fully autonomous drones capable of carrying out complex navigation tasks across a variety of domains, a thorough review of the most recent DRL algorithms, training strategies, simulation platforms, real-world applications, challenges, and future research directions is crucial.[14]

2. Review Of Literature

Sheng, Yuanyuan et al., (2024)[15] Deep reinforcement learning (DRL)-based autonomous navigation of unmanned aerial vehicles (uavs) has advanced significantly. The influence of complicated job scenarios on UAV flying performance is not taken into account by the majority of research, which assume comparatively simple task situations. In order to allow autonomous route planning for uavs in extremely dynamic and dense situations, this study suggests a DRL-based autonomous navigation algorithm. By examining the effects of UAV position and angle changes on navigation performance in complicated settings, this approach suggests a state space representation technique that includes position and angle information. In order to balance the agent's exploratory and cautious behavior during the model training process, a dynamic reward function is also built based on a non-sparse reward function. The suggested method provides the greatest autonomous navigation performance and the best flying efficiency in complicated situations, according to the findings of many comparison studies.

Samma, Hussein and Sami El-Ferik (2024)[16] Unmanned aerial vehicles (uavs) have gained popularity in recent years for a number of uses, such as surveillance, missing person searches, and package delivery. However, the presence of moving objects, such as people, makes autonomous UAV navigation difficult in dynamic situations. Furthermore, conventional deep reinforcement learning techniques need a large amount of training data and have poor learning rates in dynamic scenarios. The current work suggested an improved deep reinforcement learning technique that includes two separate learning stages—the reinforced and self-supervised—in order to maximize learning performance. The deep Q-learning network (DQN) has been put into practice and trained using the Bellmen equation's loss as a guidance throughout the reinforced learning phase. Conversely, the contrastive loss function guided the self-supervised stage, which is in charge of fine-tuning the DQN's backbone layers. The self-supervised stage's primary advantage is that it expedites the encoding of the input scene that the UAV camera has acquired. An obstacle detection model was included to improve navigation even further and lower the number of UAV crashes. We have used Blocks, an outdoor UAV-simulated environment, for experimental analysis. Both moving people and immovable items that resemble buildings are present in this setting. According to the research, navigation performance significantly improved once the self-supervised stage was implemented. In particular, the simulated UAV might go further and in the right direction to reach the destination. Furthermore, when compared to other DQN-based strategies like double DQN and dueling DQN, the study demonstrates a notable navigation performance.

Kalidas, Amudhini P et al., (2023)[17] Drones, or unmanned aerial vehicles, or uavs, have made significant strides in recent years. Drones may be used for a variety of purposes, such as disaster assistance, transportation, photography, and climate monitoring. Their great degree of effectiveness and safety in every operation is the cause of this. Although drone design aims for excellence, it is still not perfect. Drones still have a lot of difficulties when it comes to identifying and averting crashes. In this regard, this study outlines a process for creating a drone system that can function on its own without assistance from humans. Using just picture input, this work trains a drone to autonomously avoid obstacles in discrete and continuous action spaces using reinforcement learning techniques. This work is interesting since it uses several reinforcement learning approaches to thoroughly evaluate the benefits, drawbacks, and potential future research areas of obstacle detection and avoidance for drones. Three distinct reinforcement learning techniques that may help in avoiding obstacles, both moving and stationary, are compared in this study: Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Soft Actor-Critic (SAC). These techniques have shown more effective in drones. Airsim provided a virtual environment in which the experiment was conducted. To comprehend and analyze the behavior of RL algorithms for drones, a variety of training and testing scenarios were developed using Unreal Engine 4. The training results showed that SAC performed better than the other two algorithms. The least successful algorithm was PPO, suggesting that on-policy algorithms are useless in large-scale 3D landscapes with dynamic actors. Two off-policy algorithms, DQN and SAC, yielded promising results. However, in small paths and bends, DQN may not be as beneficial as SAC because of its limited discrete action area. Regarding more research, off-policy algorithms like DQN and SAC outperform on-policy algorithms like PPO in the context of autonomous drones. The results may have applications in the future for the creation of safer and more effective drones.

Doukhi, Oualid and Lee, Deok J I N (2022)[18] Numerous activities, including airborne deliveries, inspection in hazardous environments, and rescue, are anticipated to be performed by flying robots. They haven't been used much in extremely dynamic, unstructured contexts, however. This study suggests a unique method for allowing an unidentified interior or outdoor area to be explored and navigated using a micro-aerial vehicle (MAV) system fitted with a depth sensor and laser rangefinder. To combine data from many sensors installed on a car, we developed a modular deep-Q-network architecture. The proposed system, which was trained only on a 3D simulator, is capable of doing collision-free flights in the actual world. The suggested approach eliminates the need for route design, 3D mapping, and previous expert demonstrations. It uses an end-to-end convolutional neural network (CNN) to convert fused sensory data into a robot's velocity control input. The policy that was developed was contrasted with a simulation that was conducted using the traditional potential-field technique. By modeling actual sensor data, our method enables zero-shot transfer from simulation to real-world situations that were never seen during training. To show how well our technology works for safely flying in dynamic outdoor and interior conditions, a number of extensive tests were carried out.

Hodge, Victoria J et al., (2021)[19] Unmanned aerial vehicles (drones) and other mobile robots may be used for data collecting, monitoring, and surveillance in infrastructure, environments, and buildings. It is well recognized that precise and comprehensive monitoring is essential for spotting issues early and stopping them from becoming worse. This drives the need for mobile robots that are adaptable, self-governing, and capable of making decisions. These systems must have the capacity to learn by combining information from many sources. They have been task specific till recently. In this research, we develop a general navigation algorithm that directs the drone to the issue location using input from sensors on board. Accurately and quickly identifying issues is crucial in dangerous and safety-critical circumstances. Our general and flexible navigation method is implemented using long short-term memory neural networks, incremental curriculum learning, and the proximal policy optimization deep reinforcement learning algorithm. To show the accuracy and efficiency of a heuristic approach, we compare several setups. Lastly, we examine how the drone's safety may be guaranteed by evaluating how safely the drone would operate in practical situations using our navigation algorithm.

Guo, Tong et al., (2021)[20] Unmanned Aerial Vehicle (UAV) navigation is aimed at directing a UAV to the target destinations along a collision-free and efficient route without human interventions, and it plays a significant role in autonomous missions in difficult settings. The UAV navigation problem may be solved by the recently developed Deep Reinforcement Learning (DRL) techniques, but most of these techniques are unable to converge because of the enormous volumes of interactive data generated when a UAV is navigating in highly dynamic environments with many obstacles moving quickly. To address these underlying constraints, we provide an enhanced DRL-based approach in this study. We specifically create a distributed DRL framework to break down the UAV navigation job into two smaller sub-tasks, each of which is addressed utilizing a portion of the interactive data and the Long Short-Term Memory (LSTM) based DRL network. Additionally, for the UAV navigation issue, a clipped DRL loss function is suggested to tightly stack the two sub-solutions into a single integral. Comprehensive simulation results are shown to support the superiority of the suggested approach over the state-of-the-art DRL approaches in terms of convergence and efficacy.

Azar, Ahmad Taher et al., (2021)[21] Unmanned aerial vehicles, or uavs, are being used more and more in a wide range of difficult applications. Both the military and the civilian sectors are home to these applications. Intelligence, Surveillance, Target Acquisition, and Reconnaissance (ISTAR) operations, traffic patrols, remote sensing, mapping, surveillance, infrastructure inspection, animal and human rescue, and environmental monitoring are just a few examples. However, a significant degree of autonomy is required for the employment of uavs in these applications. To put it another way, uavs should be able to complete scheduled tasks under unforeseen circumstances without the need for human assistance. Numerous artificial intelligence algorithms were created to guarantee this degree of autonomy. The guidance, navigation, and control (GNC) of uavs was the focus of these algorithms. The state of the art for one subset of these algorithms—the deep reinforcement learning (DRL) techniques—was discussed in this work. We provided a full description of them, and we calculated the present limits in this field. We found that most of these DRL approaches were developed to assure steady and smooth UAV navigation by training computer-simulated surroundings. We came to the conclusion that further study is required to overcome the issues preventing their use in practical situations.

Anwar, Aqeel and Raychowdhury, Arijit (2020)[22] At the edge of the cloud, intelligent and nimble drones are quickly becoming commonplace. These drones' low power and computational capacity restrict how they may be used. In this study, we propose a Transfer Learning (TL) based method to attain a goal algorithmic performance by reducing the on-board compute needed to train a deep neural network for autonomous navigation via value-based Deep Reinforcement Learning. The Unreal Gaming Engine is used to manually create a library of realistic 3D meta-environments, and the network is trained from beginning to finish. The network is then initialized in a test environment using these learned meta-weights, and the last few fully connected layers are adjusted accordingly. To demonstrate the resilience of the technique, variations in drone dynamics and ambient features are conducted. It was shown using the NVIDIA GPU profiler that training latency and energy consumption can be decreased by 3.7x and 1.8x, respectively, without noticeably affecting performance in terms of Mean Safe Flight (MSF), or the average distance flown before a crash. Similar results were obtained when the method was tried in a real-world setting using a DJI Tello drone.

Muñoz, Guillem et al., (2019)[23] Future delivery operations are anticipated to make substantial use of drones. It is easy to navigate using satellites from the point of departure to the geolocated destination when there are no barriers in the way. Pilots must develop a flying plan to avoid recognized obstacles. However, it becomes very difficult to create a safe flight plan when they are unknown, in large numbers, or at locations that are not stable positions. Furthermore, the existing drone navigation systems may not work in areas with poor satellite signals, including inside, under forest canopy, or in urban canyons. Such difficulties may be addressed by artificial intelligence, a field of study that is becoming more and more active. Originally developed for robotics, artificial intelligence is currently mostly used for ground vehicles, but it is also being used to teach drones. The area of artificial intelligence that can teach robots is called reinforcement learning. Drones will become more intelligent via the use of reinforcement learning, ultimately becoming completely autonomous devices. This paper investigates drone delivery using reinforcement learning. The drone's only sensor is its stereo-vision front camera, which provides depth data. The drone has been taught to fly through a neighborhood with several obstacles, including homes, automobiles, wires, and trees. Additionally, a geo-fence—a virtual, invisible border that prevents drones from entering or exiting a designated region—defines the flying area. The drone must accomplish a task and stay clear of obvious impediments. The findings demonstrate that the new algorithms perform better than the old ones, not only in terms of reward but also in terms of variance reduction. The checkpoints are the second contribution. Every time a higher reward is obtained, they involve saving a trained model. Findings demonstrate how checkpoints enhance test outcomes.

Chao Wang et al., (2017)[24] Delivery by Unmanned Aerial Vehicles (uavs) is becoming popular. Using deep reinforcement learning, we solve the discrete-time continuous control problem of autonomous UAV navigation in a large-scale unknown complex environment. Using just the local surroundings and GPS signal, our approach allows uavs to travel from arbitrary departure points to destinations without the need for route planning or map building. We contend that the present recurrent deterministic policy gradient approach is inefficient and that the navigation problem is a partly observable Markov decision process (POMDP). As a result, we construct an actor-critic architecture-based policy learning method for POMDP that is quicker. We model a virtual UAV flying at a fixed height and constant speed, as well as five simulated surroundings, to confirm our hypotheses. The local environment is recognized by measuring the distances between barriers and uavs in various directions. Simulation results show that our method works well.

3. Conclusion

Deep reinforcement learning (DRL) has become a revolutionary paradigm for autonomous UAV navigation, providing strong alternatives to conventional rule-based and model-dependent control systems, as the examined literature collectively shows. From early attempts to handle partially observable environments using actor–critic architectures to advanced multi-stage, sensor-fusion, and distributed learning frameworks that improve stability, adaptability, and decision-making accuracy in extremely dynamic and uncertain conditions, a clear progression can be seen across studies conducted between 2017 and 2024. Recent studies like Sheng et al. (2024) emphasize that complicated job situations, thick obstacle fields, and frequent changes in UAV posture must all be taken into consideration for real-world UAV navigation. They demonstrate that richer environmental representations greatly enhance autonomy by introducing state-space designs that include location and angle as well as dynamic reward systems. Samma and El-Ferik (2024) also highlight the shortcomings of traditional DRL in dynamic scenarios with moving objects or humans. Their two-stage reinforced plus self-supervised learning model highlights the general trend toward hybrid learning methodologies by showing that improving the perceptual encoding step may significantly speed up training and lower collision rates. Kalidas et al.'s comparative analyses from 2023 also show that algorithm selection has a significant impact on performance: off-policy techniques like SAC and DQN are more robust in large 3D landscapes than on-policy PPO, confirming the need for algorithms with better exploration–exploitation balance and effective sample reuse.

Previous fundamental research is still important. Doukhi and Lee (2022) demonstrated that zero-shot transfer from simulation to reality—a crucial step toward reliable field deployment—is made possible by merging several onboard sensors with modular deep Q-networks. In their contribution, Hodge et al. (2021) shown that temporal context enhances hazard prediction in safety-critical contexts by putting forward generalizable navigation algorithms using LSTM-enhanced PPO and curriculum learning. In order to address the scalability issue, several studies, including Guo et al. (2021), proposed distributed DRL frameworks that break down navigation into smaller tasks, increasing network efficiency and convergence. Reviews such as Azar et al. (2021) show that despite ongoing advancements, computational limitations, unpredictability of the environment, and dependence on simulation-trained rules remain obstacles to practical implementation. This is in line with Anwar and Raychowdhury (2020), who used transfer learning to overcome computational constraints and lower onboard training costs while preserving drone performance. This increases the viability of DRL for uavs with limited resources. By demonstrating that drones can navigate complex terrains on their own using only visual depth data or local distance measurements, eliminating the need for maps or satellite-based positioning, and validating the long-term vision of fully autonomous drone delivery networks, earlier reinforcement learning applications like Muñoz et al. (2019) and Wang et al. (2017) set the foundation.

The literature shows a steady rising trend toward UAV navigation systems that are more durable, intelligent, and prepared for the actual environment. Drones will eventually be able to safely and precisely navigate crowded cities, dense forests, indoor spaces, and unpredictable environments thanks to advancements in state representation, reward engineering, sensor fusion, hybrid learning, off-policy optimization, transfer learning, and distributed architectures. Ongoing research is still necessary to address enduring issues like generalization to unforeseen circumstances, real-time computing, and simulator-to-reality gaps. When taken as a whole, these studies provide a thorough basis showing how quickly DRL-driven autonomous navigation is developing from experimental simulations to useful, significant real-world applications.

References

1. Karunanithy K, Velusamy B, Prasanth A. Remote Assessments and Aerial Imaging Using UAV for Disaster Management and Precision Agriculture with Immediate Response–A Case Study. Drones for Transportation Logistics and Disaster Management. 2025 Nov 20:371-98.
2. Tian C, Cho Y, Song Y, Park S, Kim I, Cho SY. Integration of AI with artificial sensory systems for multidimensional intelligent augmentation. International Journal of Extreme Manufacturing. 2025 Mar 27;7(4):042002.
3. Li H, Zhang Q, Zhao D. Deep reinforcement learning-based automatic exploration for navigation in unknown environment. IEEE transactions on neural networks and learning systems. 2019 Aug 6;31(6):2064-76.
4. Buyuktanir T, Aktas MS. On the Use of Embedding Techniques for Modeling User Navigational Behavior in Intelligent Prefetching Strategies. Concurrency and Computation: Practice and Experience. 2025 Feb 1;37(3):e8356.
5. Fujimura K. Motion planning in dynamic environments. Springer Science & Business Media; 2012 Dec 6.
6. Wu J, Wu QJ, Chen S, Pourpanah F, Huang D. A-TD3: An adaptive asynchronous twin delayed deep deterministic for continuous action spaces. IEEE Access. 2022 Dec 2;10:128077-89.
7. Dieter TR, Weinmann A, Jäger S, Brucherseifer E. Quantifying the simulation–reality gap for deep learning-based drone detection. Electronics. 2023 May 11;12(10):2197.
8. Lee EA. Determinism. ACM Transactions on Embedded Computing Systems (TECS). 2021 May 29;20(5):1-34.

9. Mieloszyk J, Tarnowski A, Tomaszewski A, Goetzendorf-Grabowski T. Validation of flight dynamic stability optimization constraints with flight tests. Aerospace Science and Technology. 2020 Nov 1;106:106193.
10. Dana KJ, Van Ginneken B, Nayar SK, Koenderink JJ. Reflectance and texture of real-world surfaces. ACM Transactions On Graphics (TOG). 1999 Jan 1;18(1):1-34.
11. Thi HL. Advancements in Quantum Computing: Revolutionizing Sensor Fusion and Data. Intelligent Sustainable Systems: Selected Papers of worlds4 2024, Volume 4. 2025 Jul 1;1180:123.
12. Wu J, Ye Y, Du J. Autonomous drones in urban navigation: Autoencoder learning fusion for aerodynamics. Journal of Construction Engineering and Management. 2024 Jul 1;150(7):04024067.
13. Houliotis K, Oikonomidis P, Charchalakis P, Stipidis E. Mission-critical systems design framework. Advances in Science, Technology and Engineering Systems Journal. 2018 Mar 12;3(2):128-37.
14. Luan T. A comprehensive review of simulation technology: development, methods, applications, challenges and future trends. International Journal of Emerging Technologies and Advanced Applications. 2024 Jun 24;1(5):9-14.
15. Sheng Y, Liu H, Li J, Han Q. UAV Autonomous Navigation Based on Deep Reinforcement Learning in Highly Dynamic and High-Density Environments. Drones. 2024;1(2):12–20.
16. Samma, Hussein SE-F. Autonomous UAV Visual Navigation Using an Improved Deep Reinforcement Learning. IEEE Access. 2024;2(June):79967–77.
17. Kalidas AP, Joshua CJ, Quadir A, Basheer S, Mohan S, Sakri S. Deep Reinforcement Learning for Vision-Based Navigation of uavs in Avoiding Stationary and Mobile Obstacles. Drones. 2023;1(2):5–14.
18. Doukhi O, Lee DJIN. Deep Reinforcement Learning for Autonomous Map-Less Navigation of a Flying Robot. IEEE Access. 2022;10(August):82964–76.
19. Hodge VJ, Hawkins R, Alexander R, Hodge VJ, Hawkins R. Deep reinforcement learning for drone navigation using sensor data. Neural Comput Appl [Internet]. 2021;33(6):2015–33. Available from: https://doi.org/10.1007/s00521-020-05097-x
20. Guo T, Jiang N, Li B, Zhu X, Wang Y, Du W. UAV navigation in high dynamic environments : A deep reinforcement learning approach. Chinese J Aeronaut [Internet]. 2021;34(2):479–89. Available from: https://doi.org/10.1016/j.cja.2020.05.011
21. Azar AT, Koubaa A, Mohamed NA, Ibrahim HA, Ibrahim ZF, Kazim M, et al. Drone Deep Reinforcement Learning : A Review. Electron Rev. 2021;1(2):1–30.
22. Anwar A, Raychowdhury A. Autonomous Navigation via Deep Reinforcement Learning for Resource Constraint Edge Nodes Using Transfer Learning. IEEE Access. 2020;1(2):1–9.
23. Muñoz G, Barrado C, Çetin E, Salami E. Deep Reinforcement Learning for Drone Delivery. Drones Artic. 2019;1(3):3–9.
24. Chao Wang, Jian Wang, Xudong Zhang And XZ, Department. AUTONOMOUS NAVIGATION OF UAV IN LARGE-SCALE UNKNOWN COMPLEX ENVIRONMENT WITH DEEP REINFORCEMENT LEARNING Chao Wang , Jian Wang , Xudong Zhang , And Xiao Zhang. Glob 2017. 2017;1(2):858–62.