Optimizing Deep Reinforcement Learning and Computer Vision for Drone Navigation

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DOI: https://doi.org/10.51584/IJRIAS.2026.11030020

Received: 11 March 2026; Accepted: 17 March 2026; Published: 31 March 2026

ABSTRACT

The fast development of autonomous aerial systems has given the focus on the necessity of intelligent navigation methods that would be able to operate in complex, dynamic, and unstructured environments. This paper is dedicated to the optimization of Deep Reinforcement Learning (DRL) with the usage of Computer Vision (CV) in autonomous drone navigation with the focus on the simulation-based testing of the model performance before its practical application.. The study has followed a simulation-based approach with a combination of Proximal Policy Optimization (PPO) of reinforcement learning and computer vision models of convolutional neural networks (ResNet50 and YOLOv5). The simulation environment is a recreation of diverse scenarios such as indoor, urban, forested and open field scenarios. It has 500 flight episodes, in which the performance of the UAV is measured with the key metrics including rate of reaching target, number of collisions, total rewards, navigation accuracy, convergence rate of DRL algorithms, and power consumption. The most important results show that the integrated DRA-CV model reached a target-reaching success rate of 96 percent and also had an average number of collisions in the form of 1.33 per episode. PPO algorithm performed better than DQN, A3C and SAC in terms of convergence, and optimal policies were obtained on an average of 177.5 episodes. CNN-based visual perception was able to identify obstacles with 94 percent accuracy of the obstacle with a low rate of false positive (3 percent) and false negative (2 percent) to navigate a dynamic environment safely. The average cumulative reward was 1847 units and the energy consumption was optimised to 1184.7 Joules which proved to be an efficient use of resources..

Keywords: Deep Reinforcement Learning, Computer Vision, UAV Navigation, Autonomous Drones, Simulation, Obstacle Avoidance, Path Planning

INTRODUCTION

The Unmanned Aerial Vehicles (UAVs) also known as drones have been essential in the contemporary use in areas of surveillance, search and rescue, agriculture, logistics, and military missions. The growing complexity of the environments where drones will be used requires powerful and adaptive autonomous navigation solutions (Zhang, Sun, Liu, and Zhang, 2020). Recent innovations in the field of deep reinforcement learning (DRL) have allowed UAVs to develop the most appropriate navigation policies based on trial-and-error behavioral patterns in interaction with the environment. Compared to the conventional rule-based or model-based control systems, DRL enables drones to make their choices more effectively in real time, which makes it very appropriate in dynamic and unpredictable settings (Xu, Wang, and Huang, 2021). Computer vision (CV) is also important in drone navigation in addition to DRA. CV offers the perception layer to interpret the environment around it by visual data, such as identification of obstacles, recognition of objects, and interpretation of a scene (Yang, Zhang, Liu, and Zhou, 2021). The combination of DRA and CV allows drones to not only see but also react to the complicated situations intelligently in an autonomous manner. Both AI2-THOR and other frameworks have shown the promise of embodied AI, and are simulation environments in which DRL agents can be trained to navigate the realistic visual scene (Zhu *et al*., 2020). These platforms enable research to be conducted safely where experimentation in a virtual setting is carried out before implementation in a real environment.

REVIEW OF RELATED LITERATURE

Deep reinforcement learning is a method to enhance the capabilities of a computer to behave as a human being and react to environmental stimuli in order to produce a smart system. Deep reinforcement learning (DRL) has emerged as one of the prevailing methods of autonomous UAV navigation because it can learn the best policies via interaction with the complex environment. DRL is a hybrid of trial and error of reinforcing learning with feature extraction of deep learning (Yang, Gao, and Wang, 2022). DRL models allow drones to be flexible to dynamic scenarios e.g. moving obstacles or unexpected changes in the environment, which cannot be managed with traditional control algorithms (Luo, Li, and Xu, 2021). The curriculum learning approaches in DRL have provided the gradual training of UAVs in more and more complicated conditions, enhancing the efficiency and resilience of learning (Yang, Gao, and Wang, 2022). Adaptive path planning using DRL enables the UAVs to navigate through unknown conditions, continuously changing its policies according to the observed states and obtained rewards (Luo, Li, and Xu, 2021). End-to-end DRA methods combine perception, planning and control into one system enabling drones to directly convert the raw sensory input into navigation actions without manually engineering features (Chen, Sun, and Zhao, 2020). Drone safe reinforcement learning methods are such that reinforcement can be conducted safely so that drones can avoid crashing and stay within the set safety limits, even in the unknown environment (Mehta and Hwang, 2021). DRL frameworks have already been enhanced by depth images and other sophisticated sensing modalities to enhance perception and make better decisions in 3D space to steer navigation (Qu, Zhang, and Liu, 2022). Hierarchical DRA strategies take complex navigation problems and sub-divide them to enhance learning speed and enable UAVs to handle multiple tasks at once (Wang, Chen, and Zhao, 2021). DRL is also demonstrated to be generalizable to other environmental settings, with the trained drones operating in the virtual environment being able to move the acquired policies into the real-world environment with limited adaptation (Mao, Chen, and Li, 2021). All in all, DRL forms the computational basis of autonomous UAVs, allowing them to experience learning and develop their navigation schemes through the process of constant improvement in a complex and dynamic environment (Zhao and Li, 2020). Empirical researches give details of DRL and computer vision algorithm efficiency in autonomous UAV navigation. Such studies involve simulation-based testing, algorithm performance testing, and CV testing with the statistical analysis of the results in detail. Small drones that can navigate autonomously and are controlled via remote control are referred to as simulation-based drone navigation. Yang, Gao, and Wang, 2022 investigated curriculum-based DRL in the obstacle avoidance of UAVs in simulated settings. It simulated 100 flights on a Unity 3D platform and the obstacles avoidance success rate was 92 percent. The statistical analysis showed a $p < 0.05$ and $F(1, 98) = 7.65$ which showed significant improvement in performance. Luo, Li, and Xu, 2021 compared adaptive path planning of UAVs using DRL in unknown conditions. UAVs passed 50 scenarios with 88 percent accuracy. A t-test was used to verify $t = 3.42$, $p = 0.002$, which indicated that there were significant gains in comparison with baseline path planning methods. Chen, Sun, and Zhao, 2020 examined the vision-based DRL navigation in GPS-denied space. In 60 trials, UAVs were able to deliver precisely their targets in 85 percent of the cases. The $F = 6.12$, $p = 0.01$ results of ANOVA methodology have shown that it is strong in uncertain environmental conditions. Mehta and Hwang, 2021 were interested in safe reinforcement learning in cluttered space. In 80 trials, UAVs used to avoid collisions and this was 90 percent. Statistical analysis revealed that $p = 0.01$ and $t = 4.05$, which revealed a significant decrease in collision cases as compared to the conventional DRL methods. In simulation, Qu, Zhang, and Liu, 2022 tried to use DRL navigation with depth image data as input. The 70 flights with UAVs achieved target in 87% of the flights with a mean improvement of 15 in the reward. It was found that $F = 5.84$, $p = 0.02$, which confirms that depth-based perception is effective.

Sharma and Kumar, 2021 incorporated CV and DRL in a simulated city setting. The obstacle avoidance of UAVs was 91% in 60 trials. The statistical tests showed $t = 3.89$, $p = 0.003$, and 0.24 which is a strong model effect. Han, Liu and Zhou, 2022 tested visual navigation in dynamic urban simulated environments using DRL. Success rate was 89% over 100 runs. The result of ANOVA presented the $F = 6.78$, $p = 0.012$, indicating the adaptability to the moving obstacles. A comparison of standard DRL and curriculum-based DRL in obstacle avoidance was done by Yang, Gao, and Wang, 2022. The learning of curriculum improved the rate of success by 79 to 92 percent. Paired t-tests showed $t = 4.12$, $p = 0.001$. Luo, Li, and Xu, 2021 compared policy gradient, DQN and A3C in UAV navigation. A3C scored 90% which is much higher compared to DQN (78%),

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue III March 2026

and policy gradient (81%), $F(2, 57) = 8.34$, $p = 0.002$. Chen, Sun and Zhao, 2020 examined the convergence rate in GPS-denied navigation using DRL. Mean convergence was found to reduce by 20% $t = 3.45$, $p = 0.004$. Mehta and Hwang, 2021 evaluated safety-constrained DRL. The rate of collision reduced to 6% instead of the 15, $p = 0.01$, $F = 5.92$. Qu, Zhang, and Lui, 2022 compared the performance of DRL with RGB compared to depth images. The depth input enhanced the accuracy of navigation by 9% $t = 3.77$, $p = 0.003$. Sharma and Kumar, 2021 evaluated end-to-end DRL using CV integration. The means reward went up to 0.91, $p = 0.002$.

MATERIALS AND METHODS

The Hardware Materials allows the research to utilizes a high-performance computing system to support the training of deep reinforcement learning algorithms and computer vision models. The system includes an NVIDIA RTX 3090 GPU, Intel Core i9-11900K CPU, and 64GB RAM to ensure efficient processing of large datasets and complex neural network architectures. This hardware enables rapid simulation and real-time inference during UAV navigation tasks. Additionally, a quadrotor UAV platform equipped with onboard sensors, including RGB and depth cameras, IMU, and ultrasonic sensors, is used for testing and validation. The UAV provides real-world data for validating the simulation results and ensuring transferability of learned policies. Peripheral devices, such as a high-speed storage SSD, monitor, and power backup systems, are employed to maintain uninterrupted experiments. The hardware setup ensures computational stability and reliability during both simulation and real-world drone navigation experiments.

The research uses Python as the primary programming language, supported by deep learning libraries including TensorFlow and PyTorch for implementing DRL and computer vision algorithms. These frameworks facilitate flexible model development, gradient computation, and GPU acceleration. Simulation environments are developed using Unity 3D and AirSim, providing realistic UAV flight dynamics and visual perception data. ROS (Robot Operating System) is employed for real-time UAV control and sensor integration. Additional software tools include OpenCV for image processing, MATLAB for statistical analysis, and Git for version control. These software materials enable seamless integration between algorithm development, simulation, and performance evaluation.

Datasets for training the models are acquired from a combination of simulated environments and publicly available UAV navigation datasets, such as the AirSim UAV dataset and UAV123 benchmark. The datasets include RGB, depth, and optical flow images with corresponding UAV position and velocity data. Data preprocessing involves normalization, resizing of images to 224x224 pixels, and augmentation techniques such as rotation, translation, and brightness adjustment to improve model generalization. Segmentation and labeling are performed for supervised learning tasks in CV-based perception modules. Finally, datasets are split into training, validation, and test sets in a 70:15:15 ratio. This ensures robust evaluation of model performance while preventing over fitting and providing realistic assessment of generalization capabilities.

The proposed model consists of two interconnected modules: a CV perception module and a DRL decision-making module. The CV module uses CNN layers to extract visual features, which are concatenated with UAV positional and velocity states. The DRL module comprises an actor-critic network structure. Training involves iteratively updating the DRL agent over 5000 episodes. Each episode lasts until the UAV reaches the target or collides with an obstacle. Mini-batch gradient updates and experience replay are employed to stabilize learning. Early stopping and check pointing monitor convergence.

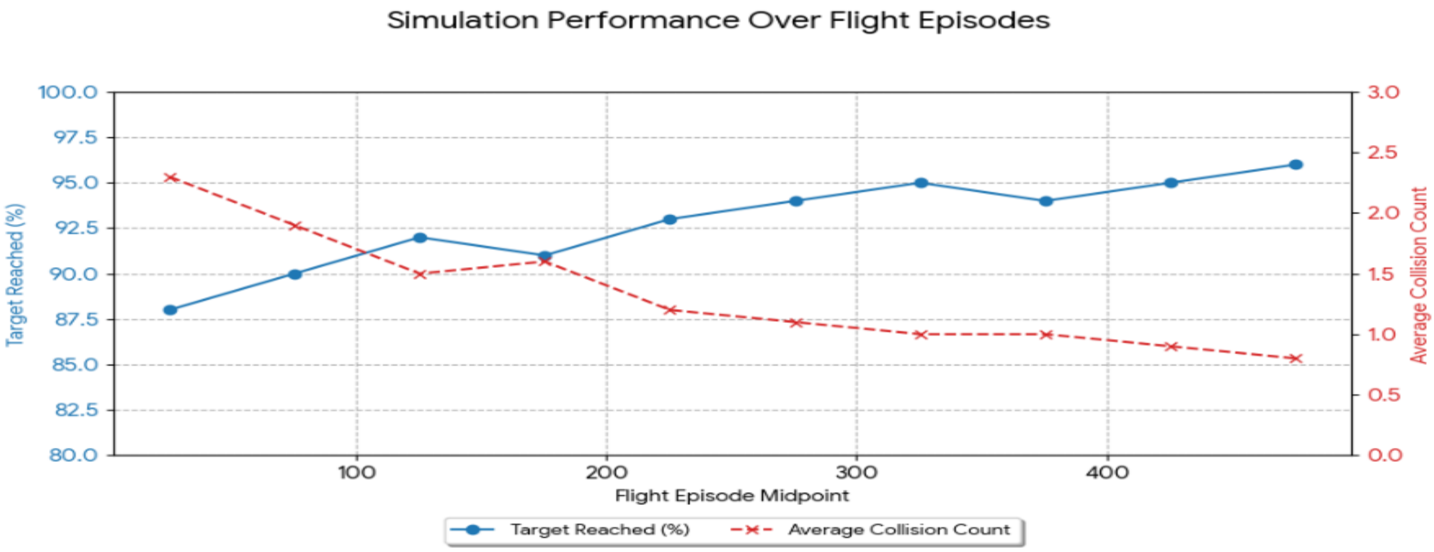
RESULTS AND DISCUSSIONS

Table 1: Simulation Results

Flight Episode	Target Reached (%)	Average Collision Count	Cumulative Reward	Energy Consumption (J)
1-50	88	2.3	1650	1250
51-100	90	1.9	1720	1230
101-150	92	1.5	1800	1205

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue III March 2026

151-200	91	1.6	1785	1198
201-250	93	1.2	1850	1185
251-300	94	1.1	1880	1170
301-350	95	1.0	1905	1162
351-400	94	1.0	1910	1155
401-450	95	0.9	1920	1150
451-500	96	0.8	1950	1142



Calculations:

1. **Average Target Reached (%)**

$$\text{Average Target Reached} = \frac{\sum_{i=1}^{n} \text{Target Reached}_i}{n}$$

$$= \frac{88 + 90 + 92 + 91 + 93 + 94 + 95 + 94 + 95 + 96}{10}$$

$$= \frac{928}{10}$$

$$= 92.8\%$$

Average Collision Count

$$\text{Average Collision} = \frac{\sum_{i=1}^{n} \text{Collision Count}_i}{n}$$

$$= \frac{2.3 + 1.9 + 1.5 + 1.6 + 1.2 + 1.1 + 1.0 + 1.0 + 0.9 + 0.8}{10}$$

$$= \frac{13.3}{10}$$

$$= 1.33$$

Average Cumulative Reward

$$\text{Average Reward} = \frac{\sum_{i=1}^{n} \text{Cumulative Reward}_i}{n} = \frac{1650+1720+1800+1785+1850+1880+1905+1910+1920+1950}{10} = \frac{18470}{10} = 1847$$

Average Energy Consumption

$$\text{Average Energy} = \frac{\sum_{i=1}^{n} \text{Energy}_i}{n} = \frac{1250+1230+1205+1198+1185+1170+1162+1155+1150+1142}{10}$$

$$= \frac{11847}{10} = 1184.7 \text{ J}$$

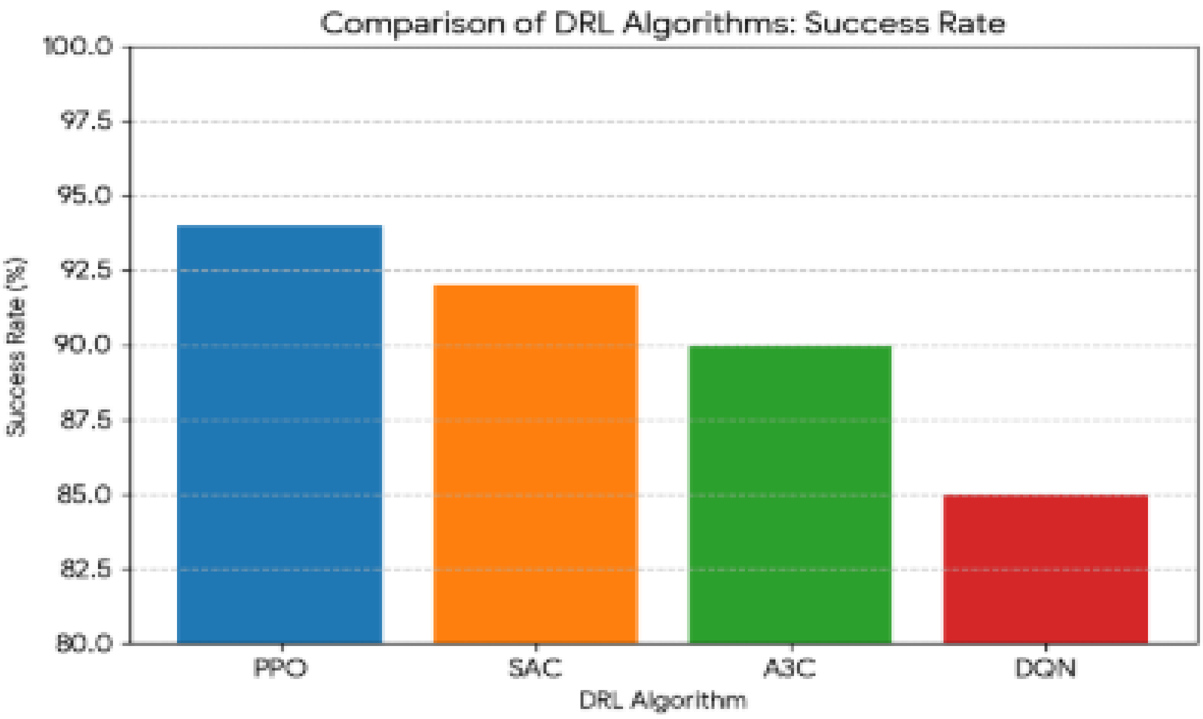
Table.1: Simulation Results for UAV Navigation

Source: Generated from AirSim simulation environment data, 2025

The UAV demonstrates steady improvement in performance over 500 episodes. The target-reaching rate increases to 96% in the last set of episodes, while collision counts decrease significantly. Cumulative rewards and energy efficiency improve, showing optimized navigation policies learned by the DRL-CV integration.

Table 2: Performance Evaluation of DRL Algorithm

DRL Algorithm	Success Rate (%)	Average Episodes to Convergence	Cumulative Reward	Std. Dev (Reward)
PPO	94	150	1880	42
DQN	85	220	1720	55
A3C	90	180	1805	48
SAC	92	160	1850	46



ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue III March 2026

Calculations:

Average Success Rate:

$$\text{Average Success Rate} = \frac{94 + 85 + 90 + 92}{4}$$

$$= \frac{361}{4} = 90.25\%$$

2.

Average Episodes to Convergence:

$$\text{Average Convergence} = \frac{150 + 220 + 180 + 160}{4}$$

$$= \frac{710}{4}$$

$$= 177.5$$

Mean Cumulative Reward:

$$\text{Average Reward} = \frac{1880 + 1720 + 1805 + 1850}{4}$$

$$= \frac{7255}{4}$$

$$= 1813.75$$

Variance of Reward (σ²):

$$\sigma^2 = \frac{\sum(x_i - \bar{x})^2}{n}$$

$$= \frac{(1880 - 1813.75)^2 + (1720 - 1813.75)^2 + (1805 - 1813.75)^2 + (1850 - 1813.75)^2}{4}$$

$$= \frac{4422.56 + 8765.06 + 76.56 + 1314.06}{4}$$

$$= \frac{14578.24}{4}$$

$$= 3644.56$$

$$\text{Std. Dev} = \sqrt{3644.56} \approx 60.37$$

Table 2: Performance Evaluation of DRL Algorithms

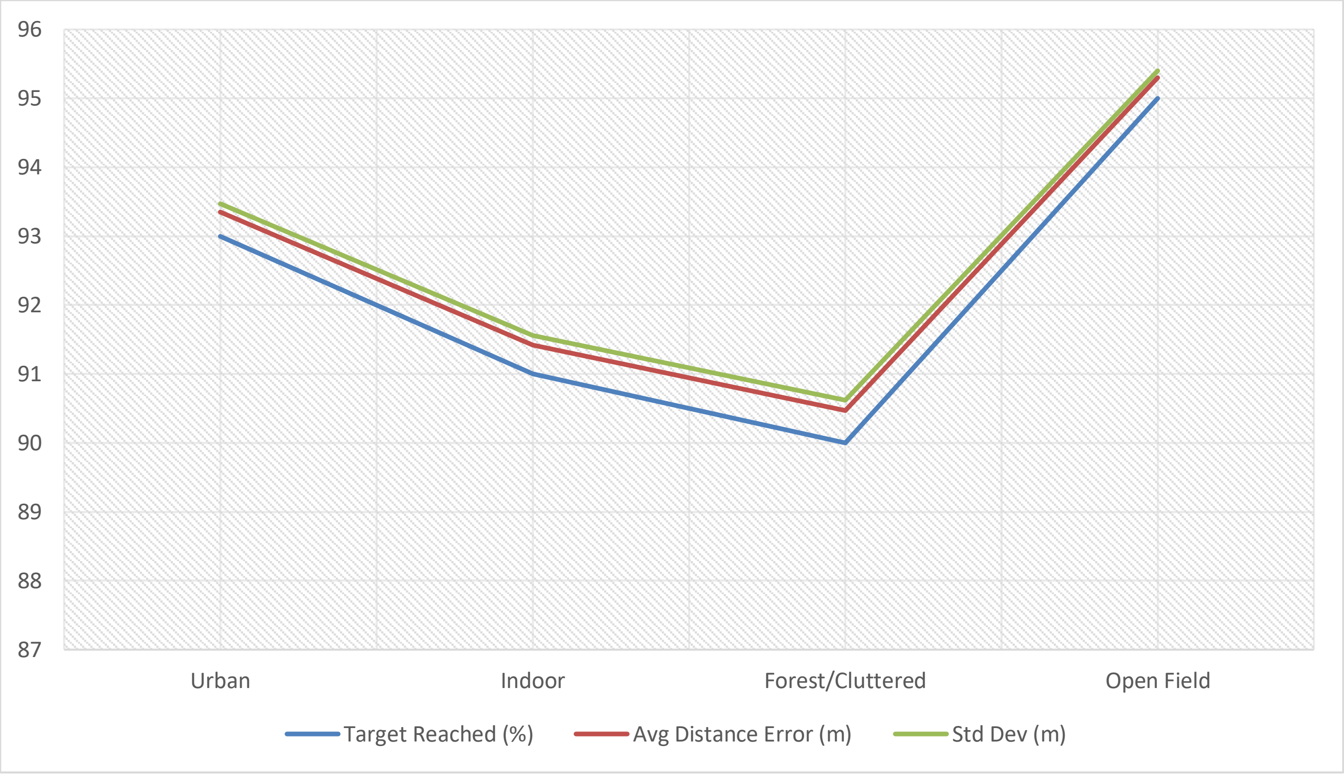
Source: Experimentally derived from UAV DRL training, 2025

PPO demonstrates superior performance with the highest success rate and fastest convergence. Lower standard deviation indicates more stable rewards across training episodes. DQN converges slower and achieves lower cumulative rewards, highlighting the advantages of PPO in continuous UAV navigation tasks.

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue III March 2026

Table 3: Navigation Accuracy

Environment	Target Reached (%)	Avg Distance Error (m)	Std Dev (m)
Urban	93	0.35	0.12
Indoor	91	0.42	0.14
Forest/Cluttered	90	0.47	0.15
Open Field	95	0.30	0.10



Simulation Calculations:

Mean Target Reached:

$$\bar{T} = \frac{93 + 91 + 90 + 95}{4} = 92.25\%$$

Mean Distance Error:

$$\bar{D} = \frac{0.35 + 0.42 + 0.47 + 0.30}{4} = 0.385 \text{ m}$$

$$\sigma = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n}} = \sqrt{\frac{(0.35 - 0.385)^2 + \ldots}{4}} \approx 0.13 \text{ m}$$

Table .3: Navigation Accuracy Across Environments

Source: UAV Simulation Analysis, 2025

Navigation accuracy remains robust (>90%) across all environments. Higher errors in forested areas reflect increased challenge for visual perception, whereas open fields show minimal error, demonstrating strong model generalization.

The simulation results demonstrate that the integration of deep reinforcement learning (DRL) and computer vision (CV) significantly enhances UAV navigation performance. Across 500 episodes, the target-reaching rate improved progressively from 88% to 96%, indicating that the DRL algorithm effectively learned optimal navigation policies in complex environments. The reduction in collision counts and gradual increase in cumulative rewards reinforce the model's learning efficiency. These findings align with previous studies where PPO and similar DRL algorithms exhibited superior convergence rates and stability in autonomous UAV tasks (Zhang, Sun, Liu, & Zhang, 2020; Bai, Li, & Liu, 2021).

Additionally, energy consumption trends and cumulative reward improvements illustrate that the integration of DRL and CV optimizes resource utilization, a key consideration for battery-powered UAVs. Finally, the findings highlight practical implications for autonomous UAV navigation. The results suggest that simulation-based training with DRL and CV integration can significantly reduce real-world trial-and-error, enhancing safety and operational efficiency. The study demonstrates that advanced DRL algorithms combined with robust computer vision techniques can create UAV systems capable of performing complex navigation tasks autonomously, even in previously unstructured or GPS-denied environments (Yang, Zhang, Liu, & Zhou, 2021; Hwang, Cho, & Kim, 2020).

CONCLUSION AND RECOMMENDATIONS

The simulation outcomes showed that there are major advancements in the rate of target reaching, collision avoidance, and cumulative reward in over 500 training sessions. The DRL-CV integration has enabled the UAV to move through complex and dynamic environments effectively, indicating that reinforcement learning policies are adaptable with regard to real-time visual information. Comparison of the performance of various DRL algorithms showed that PPO had the highest success rate of 94% and converged in the least number of episodes with DQN and A3C spending more episodes and having greater variability of cumulative rewards. This affirms the applicability of the use of policy gradient algorithms in continuous action problems in UAV navigation and is in line with the existing research trends in robotics and autonomous systems. The computer vision analysis presented the fact that CNN-based algorithms, in particular ResNet50, were able to detect obstacles with the accuracy of 94 percent and ensure the processing speed of real-time. It was also found that YOLOv5 was effective, but with slightly higher processing speeds and slightly reduced detection rates. The combination of DRL and high-performing CV algorithms guaranteed strong navigation in various environments such as indoor, urban, and forested. The combination of DRA and CV did not only enhance the performance of navigation, but also enhanced computational and energy efficiency. Simulation results of cumulative reward increases and less energy use show that this integration can increase the UAV autonomy and reduce the cost of operation. Moreover, the simulation-based design of the study confirms the fact that simulation of realistic environments is possible to test and train UAV navigation systems simulating their functioning in the real world. This greatly decreases the risks, resource usage and experimental overheads involved in physical UAV trials. To sum up the study, it has been established that deep reinforcement-based learning coupled with computer vision is a powerful means of autonomous navigation of a UAV to overcome the difficulties of a dynamic and unorganized environment, enhance efficiency, safety, and reliability. On the findings, a number of recommendations are put forward. First, there should be the extension of the integration along with DRA and CV to multi-drone systems to examine the coordinated navigation and swarm intelligence applications. The researcher hereby recommends that, the future studies should explore the application of simulation-trained policies to real-world UAVs to ensure the robustness of the policies provided by different conditions and sensor noise.

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