ENHANCED DRONE AUTONOMY IN CHALLENGING SCENARIOS USING REINFORCEMENT LEARNING

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Introduction:

1. Drones, also known as Unmanned Aerial Vehicles (UAVs), have been extensively utilized in their applications in surveillance, delivery service, disaster management, and environmental monitoring. They are very useful in the recent technology based industries because of their capability to work in unreachable and dangerous environments.
2. However, complete drone autonomy is not an easy task, particularly in complex and dynamic conditions. Conventional navigation systems use fixed rules and fixed algorithms that cannot adapt to unforeseen challenges or environmental changes. This drawback makes drones less efficient and reliable in the real world.
3. To address these issues, this project presents a smart system that is founded on Reinforcement Learning (RL). The drone is an independent agent in this approach, which learns through its interaction with the environment. It enhances its navigation by rewarding good deeds and punishing wrong decisions.
4. The system has the ability to process data concerning the environment and make real time decisions by incorporating deep learning methods like Convolutional Neural Networks (CNN). This increases the capability of the drone to navigate around obstacles and arrive at its destination in an efficient way.
5. In general, the project will attempt to create a highly efficient, adaptive and powerful drone navigation system that is capable of operating in adverse conditions including urban environments, forests as well as disaster environments.

Objectives:

1. To preprocess sensor and environmental data for efficient input representation.
2. To model the environment as a grid and define the drone as the autonomous agent.
3. To implement and evaluate the drone’s actions based on performance metrics in obstacle avoidance and navigation.

Methodology:

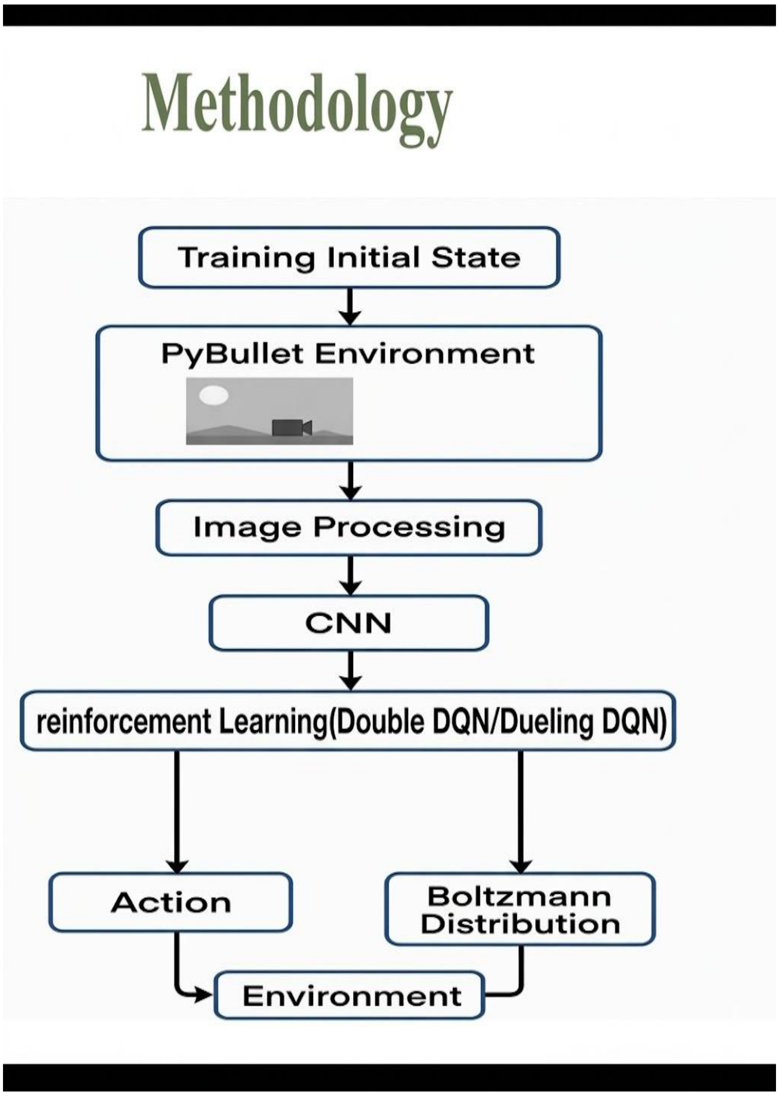

Figure 1: Flow Chart

1. The figure 1 shows that the simulation is being conducted in the PyBullet Environment which is a physics-based simulation model that gives the object realistic dynamics and interactions. PyBullet produces images of the surrounding, which are the main observations of the learning agent.
2. These raw images undergo an Image Processing stage, where they are resized, normalized, and formatted appropriately for further computation. This step reduces computational overhead while enhancing the ability of the model to extract relevant information.
3. The processed images are then passed through a Convolutional Neural Network (CNN), which extracts spatial and structural features from the environment. The resulting feature representation forms the input state for the reinforcement learning model.
4. To estimate optimal action values, the system employs either Double DQN or Dueling DQN. Double DQN mitigates Q value overestimation by decoupling action selection from evaluation, while Dueling DQN separately computes the state value and advantage function, resulting in improved stability and learning efficiency.

5. Based on the Q value predictions, the agent selects an action using either a deterministic Action Selection method (such as greedy or ϵ-greedy strategies) or a Boltzmann Distribution based method, which assigns probabilities to actions based on their estimated values. The chosen action is executed in the Environment, which returns the next observation and reward. This interaction loop continues iteratively, allowing the agent to learn an optimal control policy through trial and error over multiple episodes.

Result and Conclusion:

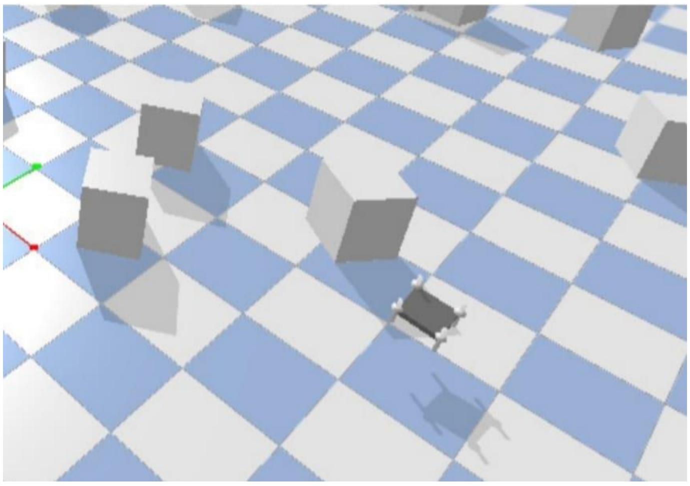

Figure 2: Drone and object

The figure 2 shows that a reinforcement learning based drone obstacle avoidance system was developed using DQN and DDQN algorithms for safe and autonomous navigation. The drone learns by interacting with its environment, using rewards to avoid collisions and optimize path efficiency. It relies on simulated sensor inputs instead of predefined maps. The trained model achieves smooth, goal directed movement with reduced collisions and shorter paths. Results show improved adaptability and robustness in complex, dynamic environments.

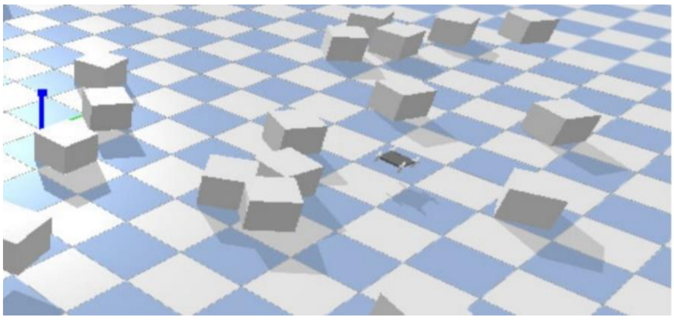

Figure 3: Drone finding path to avoid obstacles

The figure 3 shows that a reinforcement learning based drone navigation system using DQN and DDQN for autonomous movement in complex environments. The drone processes sensor data to understand obstacles and target position, selecting optimal actions in real time. A reward-based approach encourages safe, efficient paths while penalizing collisions and detours. The system improves over time, achieving smooth navigation with high reliability and adaptability.

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Future Scope:

The future scope of this project includes:

1. Deploy the trained model on real world drones for practical validation.
2. Implement multi drone coordination using multi-agent reinforcement learning.
3. Optimize energy consumption for extended flight duration and Integrate advanced
4. Sensors such as LiDAR and stereo vision for improved perception.