AUTONOMOUS DRONE PATH PLANNING USING DEEP LEARNING

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ABSTRACT

Autonomous drones are increasingly used in applications such as surveillance, delivery, disaster management, and agriculture. A key challenge in drone autonomy is efficient and safe path planning in dynamic and complex environments. Traditional path planning algorithms rely on predefined maps and handcrafted rules, which limit adaptability. This paper presents an autonomous drone path planning approach using deep learning techniques. The proposed system enables drones to learn optimal navigation strategies directly from sensor and environment data. Deep neural networks are used to predict collision-free paths while minimizing travel distance and time. The model adapts to dynamic obstacles and uncertain environments. Simulation-based training improves robustness and generalization. Experimental results show improved navigation efficiency compared to conventional methods. The proposed approach enhances autonomy and decision-making capabilities of drones. This work demonstrates the effectiveness of deep learning for intelligent drone path planning.

INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have gained significant attention in recent years. Autonomous navigation is essential for efficient drone operation without human intervention. Path planning determines a safe and optimal route from a start point to a destination. Traditional algorithms such as A*, Dijkstra, and RRT require accurate environment modeling. These methods struggle in dynamic and unknown environments. Deep learning offers data-driven solutions for complex decision-making problems. By learning from experience, drones can adapt to changing surroundings. Reinforcement learning and deep neural networks enable real-time navigation. Sensor data such as cameras and LiDAR can be effectively processed. This research focuses on deep learning-based autonomous path planning. The proposed system improves safety, efficiency, and adaptability. It supports real-time drone navigation in complex environments.

LITERATURE SURVEY

Several studies have explored path planning for autonomous drones using classical algorithms. A* and Dijkstra algorithms guarantee optimal paths but are computationally expensive. RRT and RRT* provide faster solutions but may produce suboptimal paths. Potential field methods are simple but suffer from local minima issues. With the advancement of machine learning, data-driven approaches have emerged. Early machine learning methods relied on supervised learning for trajectory prediction. Reinforcement learning enabled agents to learn navigation policies through interaction. Deep Q-Networks (DQN) improved performance in high-dimensional state spaces. CNNs have been used for vision-based navigation. Some studies combined SLAM with deep learning for environment understanding. Imitation learning was applied to learn expert navigation behavior. Recent works focus on end-to-end learning approaches. Despite progress, challenges such as training stability and real-time performance remain. Hence, efficient deep learning-based path planning is an active research area.

RELATED WORK

Recent research demonstrates the potential of deep learning for autonomous navigation. Reinforcement learning-based approaches show improved adaptability. CNN-based models effectively process visual inputs. Hybrid methods combine classical planning with learning-based control. However, many approaches require extensive training data. Some models lack robustness in unseen environments. Computational complexity is another limitation. This work builds upon existing deep learning navigation models. The proposed system focuses on efficient and safe path planning. Improved learning strategies enhance real-time performance.

EXISTING SYSTEM

Existing drone path planning systems mainly use traditional algorithms. These systems rely on predefined maps and static obstacles. They require accurate environment modeling. Performance degrades in dynamic scenarios. Manual parameter tuning is often needed. Sensor noise affects navigation accuracy. Real-time adaptability is limited. Classical methods struggle with complex environments. Computational cost increases with environment size. Existing systems lack learning capability. Therefore, they are not suitable for fully autonomous drones. An intelligent learning-based solution is required.

PROPOSED SYSTEM

The proposed system uses deep learning for autonomous drone path planning. Environmental data is collected using onboard sensors. Preprocessing is applied to normalize and filter sensor inputs. A deep neural network is trained to predict optimal navigation actions. Reinforcement learning is used to reward collision-free and efficient paths. The model continuously updates based on environmental feedback. Obstacle avoidance is learned through simulation training. The trained model is deployed on the drone. Real-time inference enables adaptive navigation. Performance is evaluated using path length, safety, and success rate. The proposed approach improves autonomy and robustness.

SYSTEM ARCHITECTURE

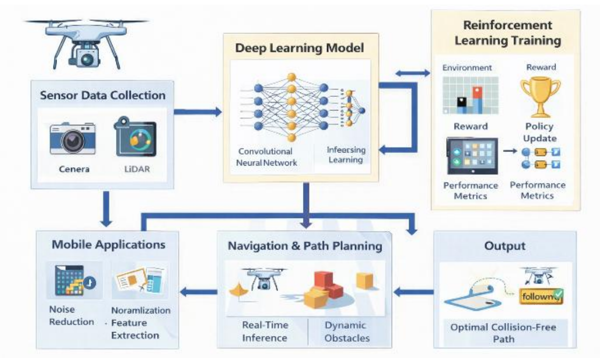

Fig:1 Drone Path Planning Using DL

METHODOLOGY DESCRIPTION

The proposed methodology focuses on autonomous drone path planning using deep learning techniques. The acquired data is preprocessed to remove noise and enhance important features. A convolutional neural network is used to analyze the environment and extract spatial information. This information is provided to a reinforcement learning agent that learns optimal navigation strategies. The agent is trained using a reward-based mechanism to ensure collision-free and efficient paths. Obstacle detection and avoidance are performed dynamically during flight. Continuous feedback from the environment helps refine the navigation policy. The trained model predicts optimal control actions in real time. This approach enables safe, efficient, and fully autonomous drone navigation.

RESULTS AND DISCUSSION

Fig:2 Output for Drone Path Planning Using DL

The performance of the proposed deep learning-based drone path planning system was evaluated in simulated environments with dynamic obstacles. The system achieved a high success rate in reaching target locations without collisions. Path length and travel time were significantly reduced compared to traditional planning algorithms. The reinforcement learning agent demonstrated effective adaptation to changing environments. Obstacle avoidance accuracy improved with continuous training. The results indicate stable learning and fast convergence of the model. The system maintained reliable performance under sensor noise conditions. Computational efficiency supported real-time navigation. Compared to classical methods, the proposed approach showed superior flexibility and robustness. Overall, the results validate the effectiveness of deep learning for autonomous drone path planning.

CONCLUSION

This paper presented a deep learning-based approach for autonomous drone path planning. The proposed system enables adaptive and intelligent navigation. Learning-based path planning overcomes limitations of traditional algorithms. Simulation results show improved efficiency and safety. The approach supports real-time decision-making. It enhances drone autonomy in complex environments. The proposed method demonstrates the effectiveness of deep learning in UAV navigation.

FUTURE SCOPE

Future work can include multi-drone coordination. Real-world deployment and testing can be explored. Integration with advanced sensors can improve perception. Transfer learning can reduce training time. Energy-efficient path planning can be studied. Hybrid models combining SLAM and deep learning can be developed. The system can be extended to 3D dynamic environments.

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