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Routing for a Network of Drones with the Aim of Search and Rescue

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Abstract

Network routing of drones for search and rescue operations is a critical challenge. This challenge arises due to the physical limitations of drones, adverse environmental conditions, and time constraints. In this paper, a novel approach for network routing of drones using the Q-Learning algorithm is proposed. This algorithm enables drones to automatically determine optimal paths in complex environments and adapt to environmental changes. Simulation results demonstrate that the Q-Learning algorithm can find shorter and more efficient routes compared to genetic algorithms. These findings highlight Q-Learning as a promising method for improving network routing of drones in search and rescue operations.

Keywords: Drone Routing-Genetic Algorithm- Q-Learning Algorithm- Network of Drones-Optimization.

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Introduction

• Problem statement

In the quest to find the lost and save lives, a network of drones comes to the aid, responding quickly and precisely to danger, saving lives from death. This involves providing an algorithm for routing a network of drones to find the shortest and fastest path and move towards it in the shortest possible time.

• Purpose

goal is to enhance the performance of drones in this critical field. By utilizing intelligent routing algorithms, drones can navigate an optimal and cost-effective path while rushing to aid humans with exemplary accuracy and speed.

• Questions/ Hypothesis

1.Drones can communicate with each other.

2.Due to weather and geographical conditions, some drones may be out of their acceptable range during search and rescue operations.

3.Several drones are used in space at the same time

4.What criteria are used to evaluate the performance of routing algorithms in search and rescue drone network?

• Background

In this regard, extensive research has been conducted in various fields related to drones and drone networks. From the diverse applications of drones to routing algorithms and drone security, scientists and experts are striving to make the most of these life-saving wings.

• Methodology

different types of drone communication networks are introduced. Finally, the fanet network is selected as the communication network between drones. Then, path planning is performed using ant colony, q-learning, differential evolution, and PSO algorithms in MATLAB software, and the results are presented.

• Conclusion

Due to their ability to optimize routes and reduce rescue time, these algorithms are the best choice for this type of mission. The average cost and average number of states explored by the Q-learning algorithm are lower than those of other algorithms. This means that this algorithm is more likely to find the best path and takes less time to do so. The Q-learning algorithm is able to learn from experience and improve its performance over time. The ant colony algorithm is able to efficiently explore large and complex search spaces. Both algorithms are able to handle dynamic environments, which is important for search and rescue missions.

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