International Journal of Scientific Research in Science and Technology
Print ISSN: 2395-6011 | Online ISSN: 2395-602X (www.ijsrst.com)
doi :https://doi.org/10.32628/IJSRST

AI Swarm Drones

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Article Info

Volume9, Issue 2

Page Number: 541-544

Publication Issue

March-April-2022

Article History

Accepted :03April2022

Published :20April2022

ABSTRACT

This paper proposes Idea and importance of a swarm of drones. In the study, inspired by the swarms in nature, drones look for the target by sensing the surrounding and communicating with each other for collision avoidance and effective co-ordination. The position for each drone is implemented using the particle swarm optimization algorithm as the swarm intelligence (A swarm-based optimization algorithm), as well as a model for the drones to take the real-world environment into consideration. In addition, the system is processed in real time along with the movements of the drones. The effectiveness of the proposed system was verified through repeated test simulations studied from various studies, including a benchmark function optimization and air pollutant search problems. The results show that the proposed system is highly practical, accurate, and robust.

Keywords: Swarm, Technology, PSO.

I. INTRODUCTION

The demand for autonomous aerial vehicles (AAV), commonly called drones, has largely increased in recent years due to their compactness and mobility, which enable them to carry out various tasks that are economically inefficient or potentially dangerous to humans effectively. For example, it is hard for humans to explore rugged mountain terrains, flooded areas, war zones or air pollution regions without drones. they have been used in various search applications, such as industrial building inspections, search and rescue operations and post-disaster area exploration autonomously. The search applications have one important factor in common search efficiency in quick time.

Previous research has focused on improving the stand-alone performance andautomation of each drone, such as localization accuracy, communication robustness, and various sensors but not on co-ordination with multiple drones. However, it is relatively expensive to handle a group of such high-end drones. Additionally, it takes a long time for a single drone to cover a broad search space. Thus, previous studies showsthe decomposition of the search space or control a number of low-cost drones into several formation patterns. The previous research successfully demonstrating the feasibility of search-by-drones, there is still room for improvement. The Important things, time and cost, it is not the best strategy to thoroughly scan every available location in the search space. so, it is more effective for drones to conduct a brief survey first and successively progress to better locations by investigating the evidence of the surroundings and communicating with each other. We can find examples of this behaviour from nature, such as ants, bees, fish, birds, and so on. They show cooperative and intelligent behaviors to achieve complex goals, which is called swarm intelligence (SI). In the area of multi-robot path planning in 2-D space, there have been several studies of approaches based on swarm intelligence. However, there is difference between mobile robots in 2-D space and drones in 3-D space. Whereas mobile robots can stand stably without any posture control and only need to be controlled by position feedback, the postures and positions of drones can be controlled based on a certain dynamic model in order to hover stably. Therefore, in this paper, swarm system for quadcopter drones is proposed by integrating the position update rule of the swarm intelligence algorithm (PSO). In the proposed system, The Study of a swarm of more than 10 drones was employed for a search mission. The swarm was controlled by a position update mechanism which included the swarm intelligence inspired from a well-known swarmbased optimization algorithm (PSO).

II. LITERATURE SURVEY

The Defense Advanced Research Projects Agency (DARPA) is experimenting with using a swarm of autonomous drones and ground robots to assist with military missions. In a video of a linear algorithm provides an effective method for maneuvering individuals in a swarm. By keeping velocity constant, the swarm of UAVs are realistically simulated. Recent test, DARPA showed how its robots analyzed two city blocks to find, surround, and secure a mock city building.

DARPA conducted its test back in June 2019, in Georgia, featuring both drones and groundbased robots. The demonstration was part of DARPA's offensive Swarm-Enabled Tactics (OFFSET) program, which is designed to eventually accompany small infantry units as they work in dense urban environments, and could eventually scale up to 250 drones and ground robots.

The Swarming Algorithms are used in the drones for the automated operations. The Particle Swarm Optimization Algorithm (PSO) and the Linear Optimization Algorithm are highly used algorithms today. PSO is focused on minimizing error between the drones and the target but changes the speed of UAVs. In addition to changing the drone's direction to head toward the target. A linear algorithm provides an effective method for maneuvering individuals in a swarm. When applying PSO to real flying objects, the constant speed changes are the main drawback. Actual UAVs should maintain a constant velocity to operate in a stable and controlled manner to prevent chaos and collisions.

Compared to the PSO, the PSO linear algorithm produces the most realistic results. The swarm does not have to move synchronously, and the UAVs move toward the target by minimizing the error in their position from the target. The error is minimized in a linear fashion since the velocity of the UAV remains constant. Linearity produces great results, and the simulated UAVs are able to find the target quickly and efficiently. The program also handles the UAVs as objects that occupy space. Each UAV has a threshold boundary distance, so they will avoid each other if they get too close. These movements allow the swarm to move toward a destination in space without collisions.

III. DESCRIPTION

There are three phases of operation. After take-off, they start a spread out phase for a fixed period of time. This first stage is used to place the drones in a good positions to start exploring the environment. This spread out of the drones in the environment is achieved by maximizing the minimum distance between them while at the same time flying within a fixed radius of the take-off area, it can obviously be implemented in a distributed and local way. Once the spread out stage finishes, the drones start the monitoring phase. The behavior of the drones continues to be the same as in the spread-out phase, they try to maximize the minimum distance between them while moving, but in this state they are also sensing the environment seeking desired object's values above a fixed alarm threshold. Also during this stage, the drones start broadcasting their sensed data through the communications channel so other agents of the system can receive it (at least those that are close enough to it). As soon as one of the drones detects an object above the threshold it enters the search stage. In this stage the plane starts collaborating with surrounding drones in order to find the object. As each plane is receiving the data sensed and broadcast by others surrounding it, it uses the data coming from the N nearest neighbors and its own sensing data to select a promising direction for continuing its search.

IV. ALGORITHM

Particle Optimization Algorithm:

Srep 1: Start.
Srep 2: Initialize the drone population by random positioning and velocity vectors.
Srep 3: Evaluate the best position of each drone.
Srep 4: Evaluate whether each drone's position is better than previous position.
Srep 5: If current position is true keep the position.
Srep 6: If false assign new best position to the drone.
Srep 7: Compute the velocity of each drone.
Srep 8: Update the position each drones for searching desired object.
Srep 9: Check whether the target found if not restart from.
Srep 10: End.

V. CONCLUSION AND RECOMMENDATIONS

In the near future, our airspace will be populated by swarms of aerial robots, performing complex tasks that would be impossible for a single vehicle. This papers reviews work that could provide the fundamental algorithmic, analytic, perceptive, and technological building blocks necessary to realize this future. The research issues discussed in this survey paper span hierarchical integration of swarm synchronization control with safe trajectory optimization and assignment, and cooperative estimation and control with perception in the loop, offering the readers a broad perspective on aerial swarm robotics. In addition, we emphasize the importance of the three way tradeoff between computational efficiency, stability and robustness, and optimal system performance. To truly address this tradeoff, we argue that it is imperative to advance beyond methods that are currently being used in autonomous drones and general swarm robotics in order to realize long-term autonomy of aerial swarm systems. One important area of further study is to develop learning and decision-making architectures that will endow swarms of aerial robots with high levels of autonomy and flexibility. We argue that such architectures will ultimately lead to reduced risk and cost as well as long-term autonomous operations. To be successful, any such architecture must provide the framework for reasoning about the wide-ranging nature of uncertainties and modeling errors, ranging from known unknowns (e.g., sensor and actuator noise) to unknown unknowns (e.g., wind disturbance, hardware failures). All of these impact the safety and robustness of algorithms and system-level functions of swarm behaviors. Furthermore, computation and communication within a swarm must be fast enough to ensure stability under model changes and mission specifications at the various timescales and bandwidths within the system. For aerial swarms systems with highly uncertain environmental models, the role of highlevel planning, decision making, and classification in flight in conjunction with low-level swarm control and estimation systems can be characterized mathematically through the properties of stability, convergence, and robustness. Various aspects of the swarm decision-making, control, and estimation should come in different timescales and hierarchical levels to exploit scalability and computational efficiency. An example of such characterization on stability would be a mathematical theorem correlating desired models and parameters to be updated on-line as well as their update or learning rates, to functions of various system features, such as sampling rate, swarm control law update rate, bandwidth of dynamics and communication, dimensions of dynamic systems, and properties of environmental uncertainties. This should also provide a guideline as to gauge how efficient and robust a particular swarm algorithm or system-level architecture is at achieving autonomy in aerial swarms. For example, distributed optimal planning requires robots to share their optimal solutions with their neighbors, up to a certain time horizon. Adding simultaneous target or task allocation to this problem further increases the required size of communicated information. It would be beneficial to combine such methods with on-line adaptation methods that can forecast the neighbors' future behavior and would, in turn, effectively reduce communication requirements. The key idea is again combining formal mathematical analysis with the hierarchical and multi-modal decomposition discussed earlier. Another important area is to establish rigorous methodologies for fault detection, isolation, and recovery to handle various potential faults occurring at sub-system levels, individual system levels, and swarm levels. As swarms are deployed to a greater extent for aggressive or agile autonomous missions, it will become necessary to create the means to exert some form of adversarial control on swarms. Such counter-swarm techniques can also be used for civilian purposes, such as maintaining law and order and herding birds and animals away from environmental hazards such as floods or wildfires.

VI. REFERENCES

[1]. Altshuler, Y.; Pentland, A.; Bruckstein, A.M. Swarms and Network Intelligence in Search; Springer: Berlin, Germany, 2018

[2]. Majumdar, A. Quadcopter Simulator. 2017. Available online: https://github.com/abhijitmajumdar/ Quadcopter_simulatorl (accessed on 19 February 2018).

[3]. Du, K.L.; Swamy, M. Particle swarm optimization. In Search and Optimization by Metaheuristics; Springer: Berlin, Germany, 2016; pp. 153–173.

[4]. T. Cieslewski, S. Choudhary, and D. Scaramuzza, "Data-efficient decentralized visual SLAM," Proc. IEEE Int. Conf. Robot. Autom., 2018.

[5]. B. Schlotfeldt, D. Thakur, N. Atanasov, V. Kumar, and G. J. Pappas, "Anytime planning for decentralized multirobot active information gathering," IEEE Robotics and Automation Letters, vol. 3, no. 2, pp. 1025–1032, 2018.