Potential of genetic algorithms in multi-UAV coverage problem

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Abstract

For a rapid area coverage multiple UAVs are often used simultaneously. However, a path planning for a UAVs group during an area coverage task is computationally challenging. In practice, heuristic algorithms are applied to solve this problem. This paper overviews approaches to an area coverage problem with a group of UAVs using genetic algorithms. The article explores modifications that may be useful for a genetic algorithm for solving the coverage problem as well as representation methods for chromosomes that reflect a path of multi-UAV. Additionally, UAV group collision avoidance strategies during area coverage are considered.

Keywords: Genetic algorithms, Coverage path, multi-UAV coverage

1. Introduction

A current rapid progress in robotics drives robotic systems into many areas of a human life including autonomous driving [1], manufacturing [2], search and rescue activities [3], agriculture [4], [5], and medical services [6]. In modern industrial applications of Industry 4.0 [7] a human–robot interaction in a shared workspace is emphasized [8], [9]. Service robotics [10] is a promising area for robots' integration covering multiple applications from education [11] and medicine [12] to entertainment [13] and advertisement [14]. A task of area coverage using mobile robots often arises in various practical applications of mobile robotics. Together with a proper scheduling, a determining of an optimal route for a mobile robot to ensure coverage of all points in a certain area while avoiding collisions with obstacles plays an important role [15].

Unmanned Aerial Vehicles (UAVs) provide an efficient solution for automating coverage and monitoring of large areas. UAVs are not constrained by obstacles on the ground and can quickly navigate through hard-to-reach areas while reducing human labor costs [16]. The use of UAVs for area coverage can be a key element in solving complex problems such as security [17], mapping [18], forest fire monitoring [19], search operations [20]. The task of covering an area with a group of UAVs attempts finding a path for each UAV such that the UAVs observe all locations of a given area without colliding with each other [21]. This task may have constraints, such as a time limit for an entire mission, safety constraints related to a minimum distance between UAVs, flight range constraints due to a battery capacity, and others.

The coverage path problem for a mobile robot is NP-hard [22] due to a need of analyzing an entire set of possible solutions, a number of which grows exponentially with increasing a complexity and a size of an area to be covered. In practice, heuristic algorithms are often employed for this task as they allow to get close to the optimal solution rather quickly, yet do not find a guaranteed optimal solution.

Genetic algorithms are popular heuristic algorithms that have a relatively simple implementation and could be easily parallelized, which is especially important when working with large solution spaces. Genetic algorithms can deal with multiple optimization criteria, which is often the case in practice. They provide a method for exploring an entire solution space to find a global optimum, which is useful in problems with many local extrema. All these turn genetic algorithms into an effective solution of the multiagent coverage problem.

2. Genetic algorithms

Genetic algorithms are based on principles of biological evolution and often are applied to search problems [23]. They model a process of natural selection to find optimal solutions. These algorithms interact with a population of potential solutions, each called an *individual*. By successively evaluating a set of solutions a new generation is created. The best solutions have a higher chance of passing on their characteristics to a next generation. Over time, solutions within the population become better adapted to a particular task.

First a genetic algorithm creates an initial population, which in typically contains random *chromosomes*. Each chromosome is a possible solution of a problem and a fitness function assigns each chromosome a numerical value that reflects its effectiveness in solving the problem. To create a next generation, individuals are selected from the population in a fixed manner. Individuals with a higher fitness for an environment have a better chance of surviving and passing their traits on to the next generation. This leads to an improvement in the population over time. A crossover operation is performed to create new offspring chromosomes. This allows new individuals to inherit the best characteristics from their parents, thus preserving them for future generations. Mutations are random changes in chromosomes of individuals that maintain a genetic diversity and periodically contribute to significant leaps in a population development. After a crossover, there is a certain probability that a mutation occurs. This mutation slightly alters chromosomes of an offspring.

3. Features of genetic operators' application in area coverage

In the area coverage problem for UAVs, it is necessary to find an optimal trajectory employed by a UAV to visit all given points of an area. Each chromosome encodes a trajectory of a UAV and the population is a set of possible UAV trajectories. In practice, chromosomes are usually sequences of integers, yet a user decides on a way of trajectory encoding within a chromosome [24].

An important feature of applying a genetic algorithm to the coverage problem is that after crossover or mutation operations, a chromosome must encode some trajectory for a UAV. Therefore, crossover and mutation operations are subjects to certain constraints.

Fig. 1 shows a two-point classical crossover operation that produces two offspring. A chromosome represents an order of visiting obstacle-free cells while covering a UAV's assigned area. If parents represent acceptable chromosomes, the offspring could contain the same genes and do not represent solutions of the coverage problem. For example, child A contains genes 2, 4, and 5, and according to the chromosome, the UAV trajectory passes through these regions twice, but it does not visit regions 1, 3, and 8.

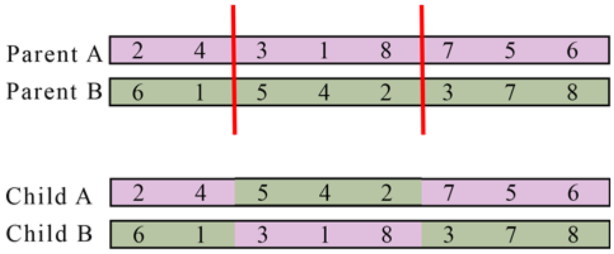

Fig. 1. An example of a crossover operation where an offspring no longer reflects a proper UAV trajectory

One solution is to modify the crossover operation. For example, using a two-point crossover from a single parent. With this method of the crossover from a single parent many children are formed and then two with a highest value of the fitness function are selected (Fig.2). In this case, each offspring reflects a proper UAV trajectory. In [25] the authors reported a four times computation acceleration of a genetic algorithm simulation using the proposed crossover method.

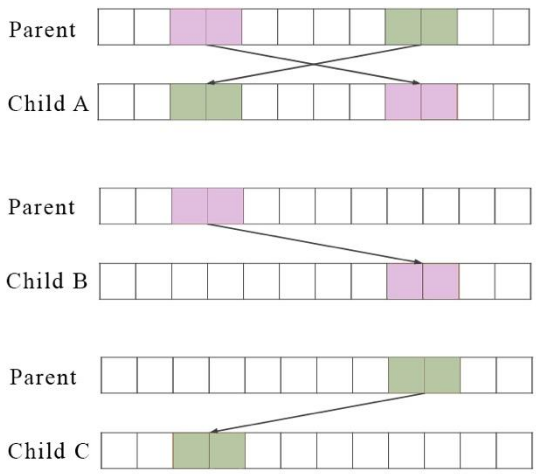

Fig. 2. An example of a crossover from one parent producing three offspring

4. Single UAV and group of UAV coverage tasks

In practice, using a group of UAVs for an area coverage increases a speed and a reliability of the procedure. Each UAV acts as a moving obstacle for other UAVs, and its route cannot be planned in isolation from the rest of the group [26]. Therefore, the genetic algorithm must consider routes of all UAVs together. A multiagent coverage problem solution is a path for each UAV in which they cover a given area together and do not collide with each other, i.e., the solution combines paths of all UAVs into a single chromosome (Fig. 3) [27].

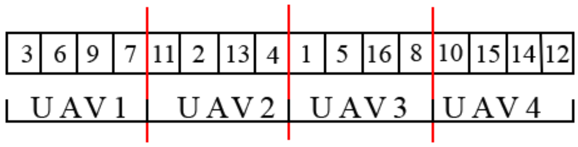

Fig. 3. A chromosome combines paths of four UAVs

5. UAV group collision avoidance strategies during area coverage

While using a group of UAVs reduces a time to complete the task, it also introduces potential risks of UAV collisions during the mission. Two strategies of UAVs' collision avoidance are discussed in this section in the context of genetic algorithms: assigning UAVs a different coverage areas and introducing a penalty for approaching other UAVs.

In the first approach, to prevent UAVs from colliding in the air, the area could be divided into equal subareas and each UAV is assigned a different subarea to cover [28]. This method allows a computation paralleling for each UAV with a genetic algorithm (as their trajectories are independent, (Fig. 4) and keeps a genetic algorithm simple. Disadvantages of this strategy include a high dependence of a resulting coverage effectiveness on a quality of an area distribution between UAVs, collision avoidance considerations while distributing UAVs (that takeoff in a common area) for the assigned subareas, and complicated splitting into subareas for a case of different survey priorities of the subareas.

In the second approach, a penalty function can be introduced to reduce a fitness function value if UAVs fly too close to each other at a coverage time [29]. This strategy is a flexible way to influence the genetic algorithm and allows using different penalty functions depending on task goals. Yet, it requires a pairwise

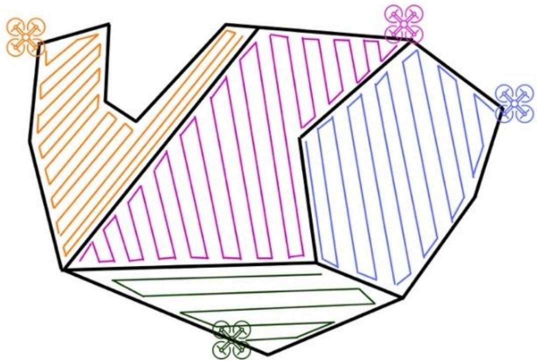

Fig. 4. Example of division of area to be covered into separate areas for each UAV

comparison of a minimum distance between each pair of UAVs and as a number of UAVs increases, a complexity increases exponentially.

6. Conclusions

Classical genetic algorithms require a task dependent adaptation in order to be employed for the problem of covering a known territory with a group of UAVs as the use of standard genetic algorithm operators in this context may destruct a chromosome that represents a trajectory of a UAVs' group. Genetic algorithms should optimize methods of representation and decomposition of a surveyed area and incorporate dynamic obstacles' collision avoidance strategies to increase the efficiency of their usage.

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References

1. J. Cheng, L. Zhang, Q. Chen, X. Hu and J. Cai, A review of visual slam methods for autonomous driving vehicles, Engineering Applications of Artifcial Intelligence, vol. 114, 2022, pp. 104992.
2. A. Gribkov, M. Morozkin, V. Kuptsov, P. Pivkin and A. Zelenskii, Industry 4.0 concepts in the machine-tool industry, Russian Engineering Research, vol. 41(7), 2021, pp. 634–635.
3. E. Magid, Simulation Tools for Urban Search and Rescue Robotics, International Conference on Artificial Life and Robotics (ICAROB 2023), 2023, pp. 4-11.
4. V. Nguyen, Q. Vu, O. Solenaya and A. Ronzhin, Analysis of main tasks of precision farming solved with the use of robotic means, in MATEC Web of Conferences, EDP Sciences, vol. 113, 2017, pp. 02009.
5. R. Iakovlev, A. Saveliev, Approach to Implementation of Local Navigation of Mobile Robotic Systems in Agriculture with the Aid of Radio Modules, Telfor Journal. vol. 12(2), pp. 92-97. 2020.
6. D. Kolpashchikov, O. Gerget and R. Meshcheryakov, Robotics in healthcare, in Handbook of Artifcial Intelligence in Healthcare, Springer, 2022, pp. 281–306.
7. R. Galin and R. Meshcheryakov, Automation and robotics in the context of Industry 4.0: the shift to collaborative robots. In IOP Conference Series: Materials Science and Engineering, vol. 537(3), May 2019, pp. 032073.
8. R. Galin and R. Meshcheryakov, Review on human–robot interaction during collaboration in a shared workspace, in International Conference on Interactive Collaborative Robotics, Springer, 2019, pp. 63–74.
9. R. Sultanov, S. Sulaiman, H. Li, R. Meshcheryakov and E. Magid, A review on collaborative robots used in industrial and service sectors. Siberian Conference on Control and Communications, (SIBCON 2022), 2022, pp. 1-7.
10. R. Belk, Ethical issues in service robotics and artifcial intelligence, The Service Industries Journal, vol. 41(13-14), 2021, pp. 860–876.

11. L. Gavrilova, A. Kotik, T. Tsoy, E. A. Martinez-Garcia, M. Svinin and E. Magid, Facilitating a preparatory stage of real-world experiments in a humanoid robot assisted English language teaching using gazebo simulator, 2020 13th International Conference on Developments in eSystems Engineering (DeSE), IEEE, 2020, pp. 222–227.
12. A. Sagitov, T. Tsoy, H. Li and E. Magid, Automated open wound suturing: detection and planning algorithm, J. Robotics Netw. Artif. Life, vol. 5(2), 2018, pp. 144–148.
13. K. J. Morris, V. Samonin, J. Baltes, J. Anderson and M. C. Lau, A robust interactive entertainment robot for robot magic performances, Applied Intelligence, vol. 49(11), 2019, pp. 3834–3844.
14. P. Bustos, L. J. Manso, A. J. Bandera, J. P. Bandera, I. Garcia-Varea and J. Martinez-Gomez, The cortex cognitive robotics architecture: Use cases, Cognitive Systems Research, vol. 55,2019, pp. 107–123.
15. E. Galceran and M. Carreras, A survey on coverage path planning for robotics, Robotics and Autonomous systems, vol. 61(12), 2013, pp. 1258-1276.
16. E. Denisov, A. Sagitov, K. Yakovlev, K. Su, M. Svinin and E. Magid, Towards Total Coverage in Autonomous Exploration for UGV in 2.5D Dense Clutter Environment, In Proceedings of the 16th International Conference on Informatics in Control, Automation and Robotics, ICINCO; SciTePress, vol. 2, 2019, pp. 409-416.
17. T. M. Cabreira, L. B. Brisolara and P. R. Ferreira Jr., Survey on coverage path planning with unmanned aerial vehicles, Drones, vol. 3(1), 2019, p. 4.
18. D. Albani and D. Nardi, V. Trianni, Field coverage and weed mapping by UAV swarms, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Ieee, 2017.
19. K. A. Ghamry and Y. Zhang, Cooperative control of multiple UAVs for forest fire monitoring and detection, 12th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), IEEE, 2016.
20. I. Maza and A. Ollero, Multiple UAV cooperative searching operation using polygon area decomposition and efficient coverage algorithms, Distributed Autonomous Robotic Systems 6. Tokyo, Springer Japan, 2007, pp. 221-230.
21. J. Muñoz, B. López, F. Quevedo, C. A. Monje, S. Garrido and L. E. Moreno, Multi UAV coverage path planning in urban environments. Sensors, vol. 21(21), 2021, 7365.
22. E. M. Arkin, S. P. Fekete and J. S. Mitchell, Approximation algorithms for lawn mowing and milling, Computational Geometry, vol. 17(1-2), 2000, pp. 25-50.
23. S. Katoch, S. S. Chauhan and V. Kumar, A review on genetic algorithm: past, present, and future, Multimedia tools and applications, vol. 80, 2021, pp. 8091-8126.
24. A. Tuncer and M. Yildirim, Chromosome coding methods in genetic algorithm for path planning of mobile robots, Computer and Information Sciences II, 26th International Symposium on Computer and Information Sciences, Springer London, 2012.
25. T. H. Pham, Y. Bestaoui and S. Mammar, Aerial robot coverage path planning approach with concave obstacles in precision agriculture, Workshop on Research, Education and Development of Unmanned Aerial Systems (RED-UAS), IEEE, 2017.
26. Y. Bai, Y. Wang, M. Svinin, E. Magid and R. Sun, Adaptive multi-agent coverage control with obstacle avoidance, IEEE Control Systems Letters 6, 2021, pp. 944-949.
27. B. Li, B. Moridian, A. Kamal, S. Patankar and N. Mahmoudian, Multi-robot mission planning with static energy replenishment, Journal of Intelligent & Robotic Systems 95, 2019, pp. 745-759.
28. R. Almadhoun, T. Taha, L. Seneviratne and Y. Zweiri, A survey on multi-robot coverage path planning for model reconstruction and mapping, SN Applied Sciences 1, 2019, pp. 1-24.
29. M. Nazarahari, E. Khanmirza and S. Doostie, Multi-objective multi-robot path planning in continuous environment using an enhanced genetic algorithm, Expert Systems with Applications 115, 2019, pp. 106-120.

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