Mathematical Biosciences and Engineering

MBE, 20(1): 18–33.
DOI: 10.3934/mbe.2023002
Received: 08 July 2022
Revised: 15 September 2022
Accepted: 19 September 2022
Published: 29 September 2022

http://www.aimspress.com/journal/MBE

Research article

Research on task allocation of UAV cluster based on particle swarm quantization algorithm

Rongmei Geng, Renxin Ji* and Shuanjin Zi

China Fire and Rescue Institute, Beijing 102202, China

* **Correspondence:** Email: jirenxin2022@163.com; Tel: +8618612100790.

Abstract: For the UAV cluster task allocation problem, the particle swarm optimization algorithm has slow convergence speed, low fitness level, easy to fall into local minimum, and can not obtain the global optimal solution. Aiming at the shortcomings of the traditional particle swarm optimization algorithm, a quantized particle swarm optimization algorithm (named QPSO method) has been designed to adapt to the task allocation problem of UAV cluster in this paper. In this algorithm, the Schrodinger equation is used to construct the quantized particle motion rule, and the Monte Carlo method is used to construct the update mechanism of the quantized particle position. The experimental results show that in the three groups of experiments of reconnaissance, attack and damage, the proposed algorithm has high adaptability, fast convergence speed, reasonable task allocation of UAVs in the cluster, efficient use of UAVs, and the performance of QPSO algorithm is obviously better than the particle swarm optimization algorithm and the genetic algorithm.

Keywords: UAV cluster; task allocation; particle swarm optimization; quantization

1. Introduction

With the development of science and technology, unmanned aerial vehicles have been widely applied as a basic platform for all kinds of disaster and accident rescue [1]. In the forest grassland fire scenario, the UAV has limited fire extinguishing agents due to the limitations of power and endurance. For situations with large fires, a single UAV is often unable to extinguish it at one time, and repeatedly loading fire extinguishing agents back and forth on the ground wastes valuable fire extinguishing time. Multiple types of UAVs form a cluster, which can deal with more complex fire rescue. For other scenarios, more aircraft combinations can be expanded and fire fighting and rescue tactics can be customized.

UAV technology is characterized by its small size, remote control, and ability to complete flight or perform tasks independently. Therefore, it has high adaptability to work in complex, unknown and unsafe situations [2]. A single UAV is limited by the number of sensors, actuators and endurance capacity it carries, and its ability to complete tasks is limited. Therefore, a UAV cluster composed of multiple UAVs has emerged to serve the overall task cooperatively [3]. There are multiple UAVs in the UAV cluster. The coordination and cooperation between UAVs greatly improves the coverage and the execution ability of complex tasks, which is an important development direction of UAV technology for the future [4].

The tasks undertaken by UAV clusters are mostly complex tasks with multiple objectives, parameters and nodes. In order to complete the overall task, the scope and number of tasks undertaken by each UAV become critical, which promotes the task allocation of UAV clusters to become the research focus in the field [5,6].

The core goal of UAV cluster task allocation is how to achieve the efficient use of each UAV individual on the premise of ensuring the completion of the overall task, that is, the balance of overall task allocation among UAVs. The task allocation research of UAV clusters has formed centralized task allocation, distributed task allocation, hybrid task allocation and other forms [7]. The key of the centralized task allocation mechanism is that the overall control information, and even the individual control information of the UAV cluster, are sent from the only control center. The UAV individuals should strictly obey the instructions of the overall control information and control center. Common models of centralized task allocation include multi-attribute, multi-task allocation model, multi-objective path optimization model, traveling salesman model, dynamic network model, etc. [8,9]. The outstanding feature of centralized task allocation is the strong global search ability. However, due to the lack of effective information exchange among UAV individuals, the real-time performance of task completion is poor and the algorithm complexity is high. The distributed task allocation mechanism not only meets the unified control of the control center, but also allows the communication and cooperation between UAV individuals. Common models of distributed task allocation include auction model and contract network model [10,11]. The outstanding characteristics of distributed task allocation are strong collaboration ability, strong local task processing ability and low algorithm complexity, but it often cannot achieve the global optimal solution. Hybrid task allocation combines centralized task allocation and distributed task allocation, and has the advantages of the two allocation methods at the same time. In the actual construction of UAV cluster task allocation algorithm, genetic algorithm, particle swarm optimization algorithm, ant colony algorithm and fish swarm algorithm are also often introduced, and the bionic intelligence is used to achieve better cooperation between UAV cluster individuals and complete the overall task goal with the best effect [12,13]. In addition, the research on autonomous communication network construction and complex path planning of multiple UAVs in the UAV field also provides a reference idea for task allocation of UAV clusters [14–18].

Based on particle swarm optimization algorithm, this paper establishes quantum particle swarm optimization algorithm (QPSO) to realize the task allocation of UAV cluster, in order to make the task allocation problem converge to a higher fitness level faster, and avoid the algorithm falling into local minimum and unable to reach the global optimal solution. The main innovation of QPSO algorithm is that it quantizes the traditional particle swarm optimization algorithm, uses the

Schrodinger equation to build the quantized particle motion law, and uses the Monte Carlo method to build the update mechanism of the quantized particle position.

2. Task allocation algorithm of UAV cluster based on quantum particle swarm optimization

2.1. Quantum particle swarm optimization

The core research content of this paper is the task allocation of multiple UAVs in the UAV cluster. The key is that each UAV can accurately reach their own task position. Therefore, assigning a reasonable location to each UAV in the cluster is the main optimization goal of this algorithm.

For multi-objective and multi-task problems, particle swarm optimization algorithm is a more targeted method. However, due to the limitations of its own theory, the convergence speed and accuracy of particle swarm optimization algorithm can not reach the optimal, and there will be a situation of falling into local optimization, so it can not reach the global optimal solution.

In order to further improve the adaptability of particle swarm optimization algorithm to UAV cluster task allocation, this paper uses quantization to construct the quantum particle swarm optimization algorithm. In quantum space, the quantized particle position and particle velocity need to be treated in the form of wave function, which is as follows:

$$\left|\phi(x,t)\right|^2 dx = \rho dx \tag{1}$$

here, x represents the position of particles, ρ representative probability density function, $\phi(x,t)$ is a wave function.

After quantization, the particle motion rule in particle swarm needs to be described by Schrodinger equation. Its probability density and probability distribution at a certain point in quantum space are shown in the following two formulas:

$$\rho(x) = \left|\phi(x)\right|^2 = \frac{1}{L} e^{-\frac{2|x-p|}{L}} \tag{2}$$

$$F(x) = 1 - e^{-\frac{2|x-p|}{L}} \tag{3}$$

here, p represents an attractor that exerts gravity on particles, L represents the depth of the potential well.

For the task allocation of UAV, it is necessary to solve the exact position of particles. Here, Monte-carlo method is used to construct the update mechanism of quantized particle position, as shown in Eq (4):

$$x = p \pm \frac{L}{2} \ln\left(\frac{1}{u}\right) \tag{4}$$

here, u is a random number with uniform value in the interval from 0 to 1.

According to the optimal solution principle of particle swarm optimization algorithm, the optimal position of the *i*-th quantized particle is:

$$p_i(t)=\begin{cases} x_i(t) & f[x_i(t)]<f[p_i(t-1)] \\ p_i(t-1) & f[x_i(t)]\geq f[p_i(t-1)] \end{cases} \tag{5}$$

The global optimal position of the whole quantized particle swarm is:

$$G(t)=p_g(t)=\begin{cases} p_g(t) & f[p_g(t)]<f[G(t-1)] \\ g(t-1) & f[p_g(t)]\geq f[G(t-1)] \end{cases} \tag{6}$$

So far, the update rule of quantized particles at time can be established, as follows:

$$x_{id}(t)=p_{id}\pm\frac{L_{id}(t-1)}{2}\ln\left[\frac{1}{u_{id}(t-1)}\right] \tag{7}$$

The update mechanism of potential well depth is as follows:

$$L_{id}(t)=2\lambda(t)\left|A_d(t)-x_{id}(t)\right| \tag{8}$$

here, $\lambda(t)$ represents the expansion coefficient varying with t, $A_d(t)$ represents the mean value of the best position, that is, the center of the best position of all particles in the whole particle swarm, and its form is as follows:

$$\begin{aligned} A(t)&=(A_1(t),A_2(t),\cdots,A_D(t)) \\ &=\frac{1}{N}\sum_{i=1}^{N}p_i(t) \\ &=\left(\frac{1}{N}\sum_{i=1}^{N}p_{i1}(t),\frac{1}{N}\sum_{i=1}^{N}p_{i2}(t),\cdots,\frac{1}{N}\sum_{i=1}^{N}p_{iD}(t)\right) \end{aligned} \tag{9}$$

2.2. UAV cluster task allocation algorithm flow

When quantum particle swarm optimization algorithm is used for task allocation of UAV cluster, each UAV corresponds to a quantized particle. The expected task to be completed is the optimization goal of particle swarm optimization algorithm, and the task location is the target location of the particle swarm optimization algorithm. The algorithm should ensure that all tasks are completed and each UAV is used with maximum efficiency, especially to avoid the situation that individual UAV tasks are overloaded and individual UAV tasks occur.

According to these requirements, and the implementation principle of quantum particle swarm optimization algorithm, the process of UAV cluster task allocation algorithm is designed, as shown in Figure 1.

As shown in Figure 1, the implementation of UAV cluster task allocation algorithm includes the following steps: First, according to the mission requirements, mission location and UAV location, the parameters of quantum particle swarm optimization are configured and initialized. Secondly, the fitness function is constructed according to the task requirements and optimization objectives, and the fitness calculation of quantum particle swarm optimization is completed. Third, calculate the local optimal position of quantum particles and the global optimal position of the whole quantum particle swarm. Fourth, update the position of quantum particles according to the preset update mechanism. Fifth, according to the latest position of quantum particles, update the local best position of each particle and the global best position of the whole particle swarm. Sixth, judge whether the iteration error at this time is less than the preset. If it is less than, the current global best position of particle swarm will be output. If the iteration error is greater than the preset, return to step 4 and repeat steps 4 and 5 until the iteration error is less than the preset. According to the output result of the above algorithm, the optimal position of the whole particle swarm is allocated to the UAV cluster correspondingly, and the position update trajectory of each quantum particle becomes the planning path of the UAV individual.

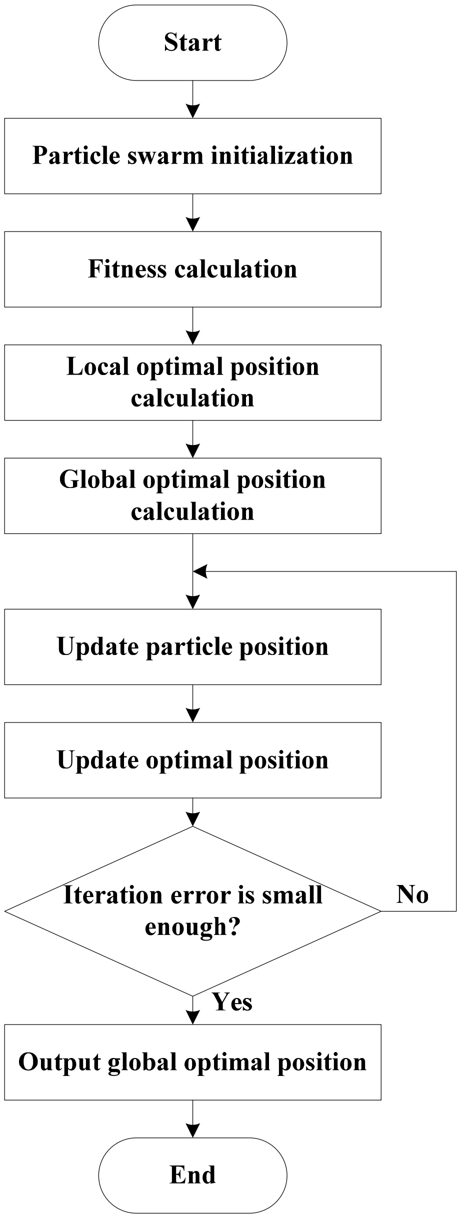


Figure 1. Task allocation algorithm flow of UAV cluster.

The pseudo code of the core part of QPSO algorithm is as follows:

QPSO Algorithm for Task Allocation of UAVs

```
1: Generate Random Particle Swarm;
2: Generate Quantum Particle Swarm by Eq (1);
3: Compute Fitness;
4: Compute Local Optimal Position by Eq (5):
5: Compute Global Optimal Position by Eq (6);
6: While Iterative_error > Threshold
7:         Update Position Particle;
8:         Update Local Optimal Position;
9:         Update Global Optimal Position;
10: Output Global Optimal Position.
```

3. UAV cluster task allocation experiment and result analysis

3.1. Experimental condition configuration

In order to verify the effectiveness of the quantum particle swarm optimization algorithm proposed in this paper for UAV cluster task allocation, experimental research is carried out next. The experiment is based on the background that unmanned aerial vehicles carry fire bombs to carry out forest fire fighting.

In the experiment, five UAVs were configured in the UAV cluster, and their corresponding numbers and coordinates are shown in Table 1.

Table 1. UAV number and coordinate configuration.

Number	X -coordinate	Y-coordinate	Z-coordinate
UAV1	36	13	26
UAV2	21	35	43
UAV3	15	28	28
UAV4	28	49	25
UAV5	35	31	20

Table 2. Task target point number and coordinate configuration.

Number	X -coordinate	Y-coordinate
Task target point A	90	16
Task target point B	33	45
Task target point C	49	27
Task target point D	47	91
Task target point E	20	27
Task target point F	50	32
Task target point G	83	69
Task target point H	14	49

In the experiment, eight task target points are configured, and their corresponding numbers and coordinates are shown in Table 2.

The tasks executed by the UAV cluster are divided into three categories, namely, fire reconnaissance task, strike task and firefighting task. The target value and overall value of the above three tasks at each task target point are shown in Table 3.

Table 3. Three types of task target values and overall target values of task target points.

Number	Reconnaissance target value	Strike target value	Fire fighting target value	Overall target value
Task target A	0.92	0.89	0.93	0.87
Task target B	0.87	0.80	0.92	0.76
Task target C	0.78	0.89	0.90	0.90
Task target D	0.90	0.78	0.86	0.73
Task target E	0.85	0.90	0.88	0.80
Task target F	0.91	0.78	0.94	0.83
Task target G	0.77	0.89	0.88	0.74
Task target H	0.92	0.93	0.95	0.89

It can be seen from the above three tables that each UAV in the UAV cluster is given the three-dimensional coordinate information in the air, while each task target point is given the two-dimensional coordinate information of the plane map. The four types of target values of each task target point are the optimization objectives of the task allocation algorithm. In the experiment, in order to form a comparison with the quantitative particle swarm optimization algorithm proposed in this paper, genetic algorithm and particle swarm optimization algorithm are also selected as the reference methods in the UAV cluster task allocation experiment. Next, the assignment experiments of reconnaissance, strike and firefighting will be carried out respectively.

3.2. Reconnaissance task allocation experiment

First, compare the fitness convergence curves of this algorithm, genetic algorithm(GA) and particle swarm optimization algorithm(PSO) when completing the task allocation of UAV cluster reconnaissance, and the results are shown in Figure 2.

It can be seen from the results in Figure 2 that in the process of UAV cluster completing reconnaissance task allocation, the fitness of the algorithm in this paper converges fastest, and the fitness value is higher when converging. The convergence speed of particle swarm optimization algorithm and genetic algorithm lags behind the algorithm in this paper, and the fitness of convergence is low.

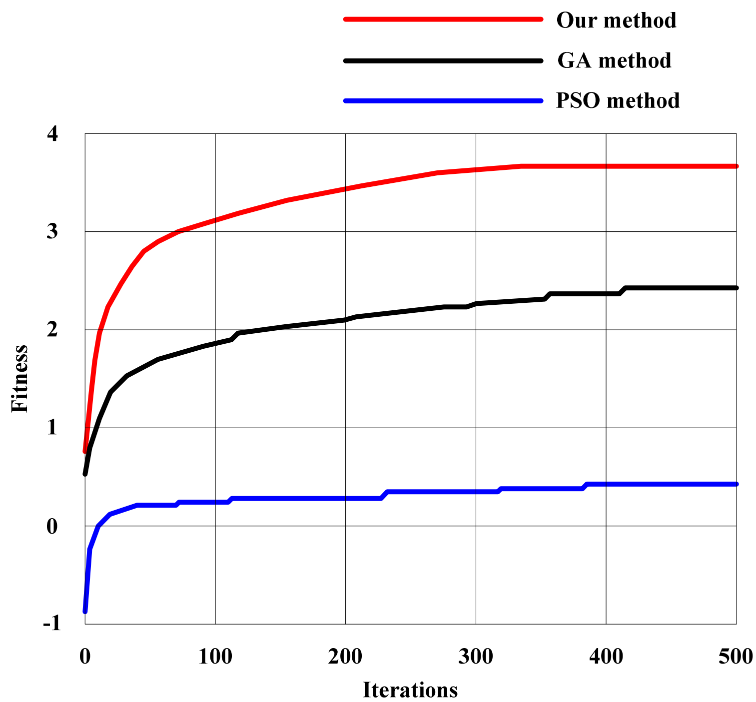
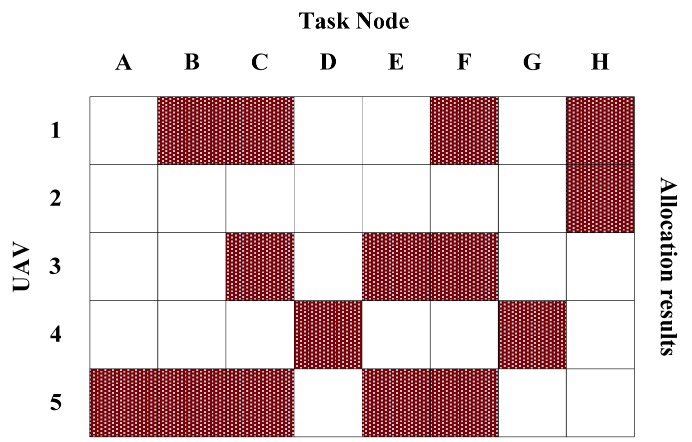


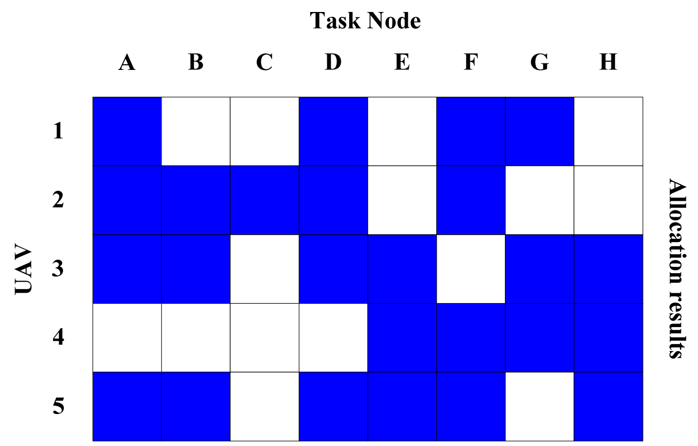
Figure 2. Comparison of reconnaissance task allocation convergence curves of three types of algorithms.

Further compare the task allocation results of UAV cluster reconnaissance completed by using three algorithms, as shown in Figure 3.

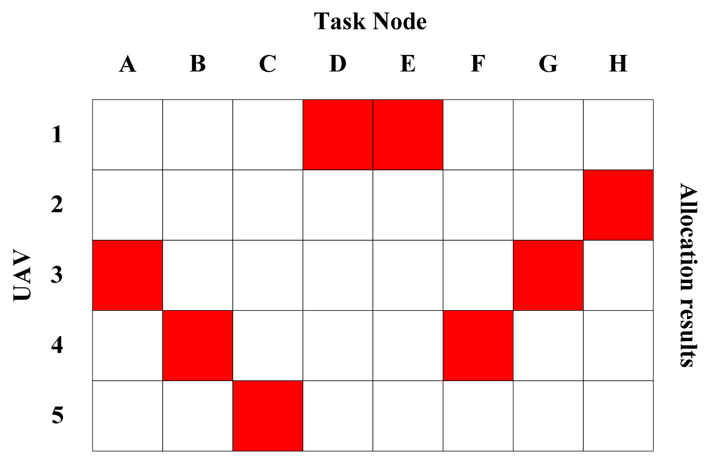
From the comparison results in Figure 3, it can be seen that the task allocation results of UAV cluster reconnaissance completed by the quantized particle swarm optimization algorithm proposed in this paper are that eight task target points are allocated to five UAVs in a relatively balanced manner. UAV 1 is responsible for the reconnaissance of D and E, UAV 2 is responsible for the reconnaissance of H, UAV 3 is responsible for the reconnaissance of a and G, UAV 4 is responsible for the reconnaissance of B and F, and UAV 5 is responsible for the reconnaissance of C, Each UAV has been used close to the maximum utility, and UAV resources have not caused waste and task overload. According to the reconnaissance task allocation results obtained by particle swarm optimization algorithm, the task allocation of each UAV is uneven. The tasks of UAV 2 are too few, while the tasks of UAV 1 and UAV 5 are too heavy. At the same time, the reconnaissance task allocation results obtained by particle swarm optimization algorithm cause the problem of multiple UAV task overload and repeated reconnaissance of task target points. Genetic algorithm also has a similar problem, and the degree of task overload and task repetition is more serious.



(a) Particle swarm optimization algorithm allocation results



(b) Genetic algorithm allocation results



(c) Algorithm allocation results in this paper

Figure 3. Comparison of reconnaissance task allocation results of three types of algorithms.

3.3. Strike task allocation experiment

First, compare the fitness convergence curves of this algorithm, genetic algorithm and particle swarm optimization algorithm when completing the task allocation of UAV cluster strike, and the results are shown in Figure 4.

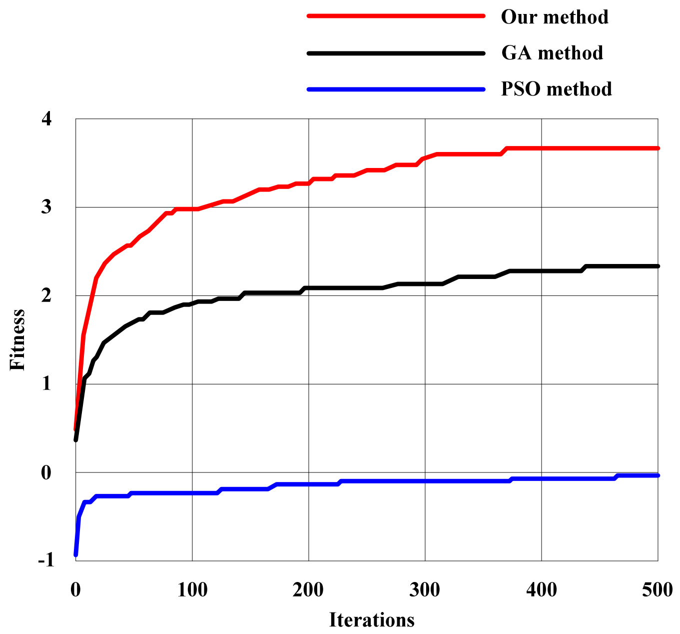
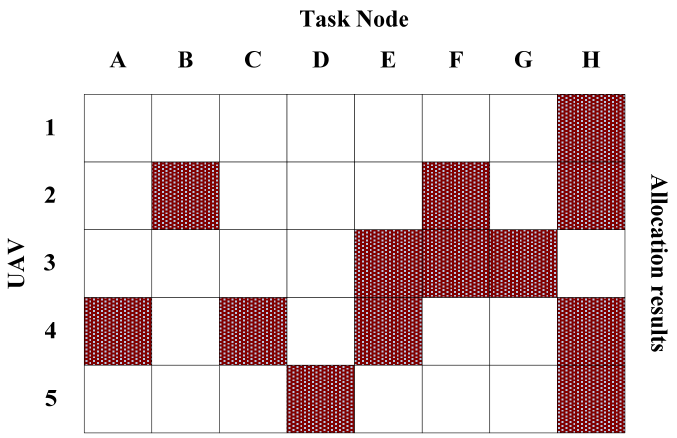


Figure 4. Comparison of attack task allocation convergence curves of three types of algorithms.

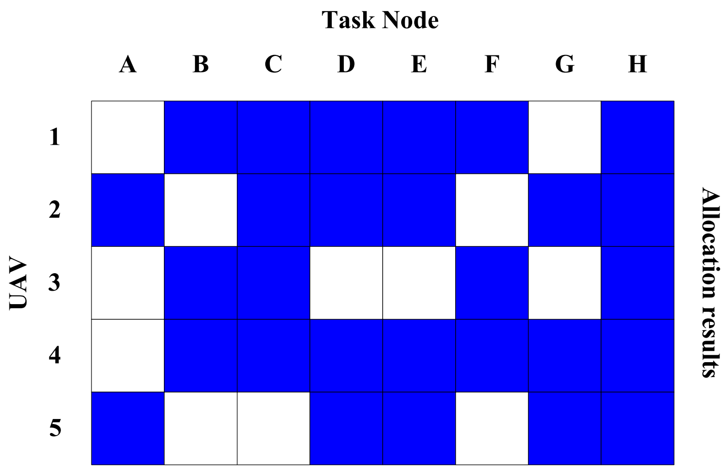
It can be seen from the results in Figure 4 that in the process of UAV cluster completing strike task allocation, the fitness of the algorithm in this paper converges fastest, and the fitness value is higher when converging. Although the convergence speed of particle swarm optimization algorithm and genetic algorithm is not far from that of this algorithm, there is a certain gap between the fitness value of convergence and this algorithm.

Further compare the task allocation results of UAV cluster attack completed by using three algorithms, as shown in Figure 5.

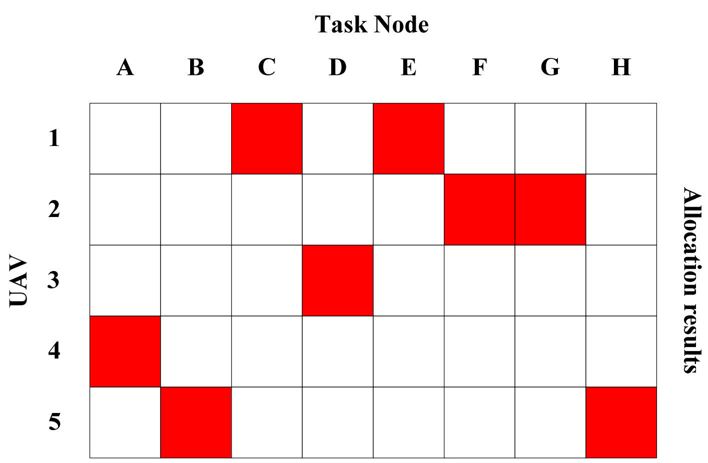
From the comparison results in Figure 5, it can be seen that the task allocation results of UAV cluster attack completed by the quantized particle swarm optimization algorithm proposed in this paper are that eight task target points are relatively evenly allocated to five UAVs. UAV 1 is responsible for the strike of C and E, UAV 2 is responsible for the strike of F and G, UAV 3 is responsible for the strike of D, UAV 4 is responsible for the strike of a, and UAV 5 is responsible for the strike of B and H, Each UAV has been used close to the maximum utility, and UAV resources have not caused waste and task overload. According to the strike task allocation result obtained by particle swarm optimization algorithm, the task allocation of each UAV is uneven. The task of UAV 1 is too few, while the task of UAV 4 is too heavy. At the same time, the strike task allocation results obtained by particle swarm optimization algorithm cause the problem of multiple UAV task overload and repeated strike at task target points. Genetic algorithm also has a similar problem, and the degree of task overload and task repetition is more serious.



(a) Particle swarm optimization algorithm allocation results



(b) Genetic algorithm allocation results



(c) Algorithm allocation results in this paper

Figure 5. Comparison of attack task allocation results of three types of algorithms.

3.4. Firefighting task allocation experiment

First, compare the fitness convergence curves of the algorithm, genetic algorithm and particle swarm optimization algorithm in completing the UAV cluster damage task allocation. The results are shown in Figure 6.

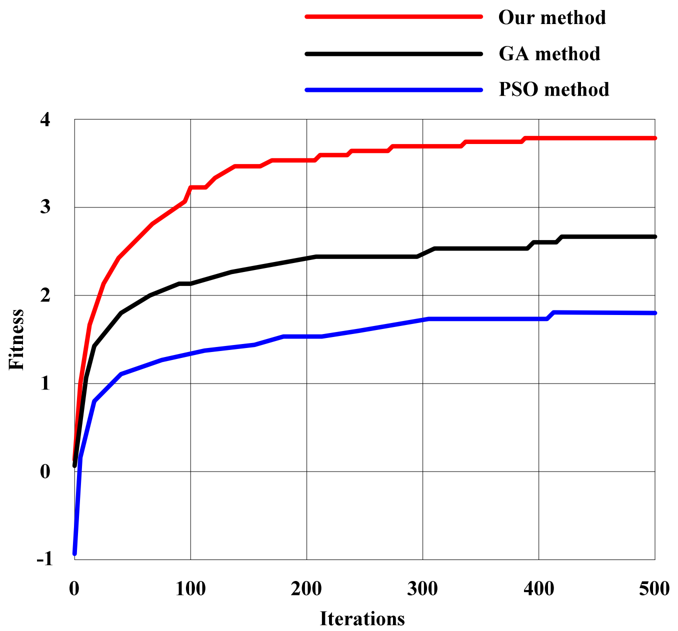
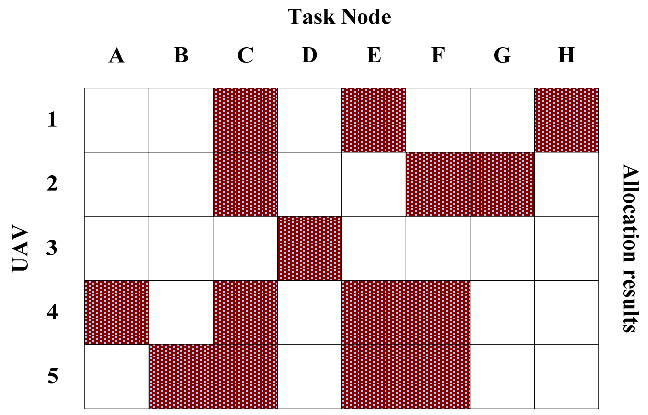


Figure 6. Comparison of convergence curves of fire extinguishing task allocation of three types of algorithms.

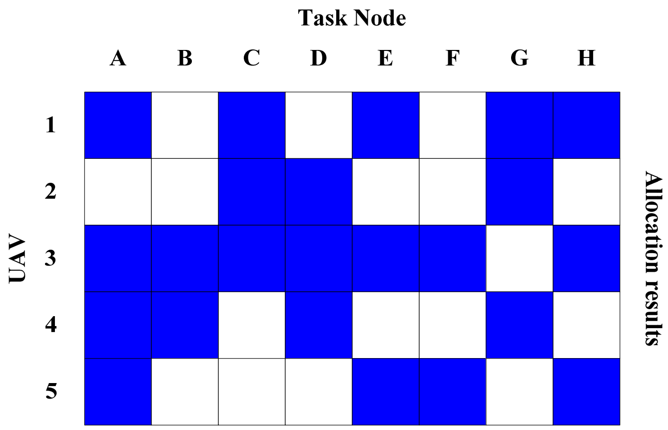
It can be seen from the results in Figure 6 that the fitness of the algorithm in this paper converges fastest and the fitness value is higher when the UAV cluster completes the fire distribution. Although the convergence speed of particle swarm optimization algorithm and genetic algorithm is not far from that of this algorithm, there is a certain gap between the fitness value of convergence and this algorithm.

Further compare the task allocation results of UAV cluster fire extinguishing completed by using three algorithms, as shown in Figure 7.

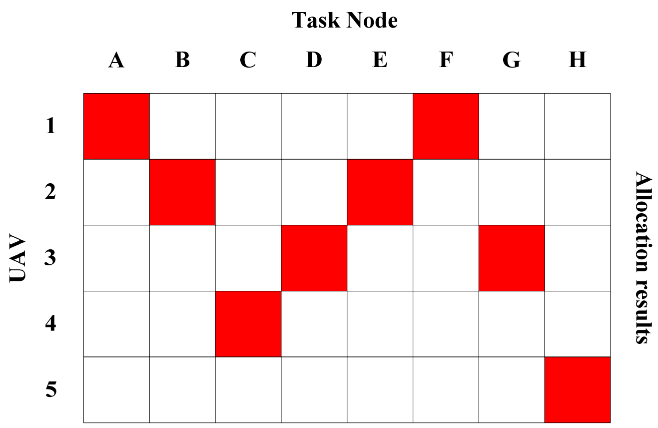
From the comparison results in Figure 7, it can be seen that the task allocation results of the UAV cluster fire-fighting, completed by the quantized particle swarm optimization algorithm proposed in this paper, are eight task target points are allocated to five UAVs in a relatively balanced manner. UAV 1 is responsible for the fire-fighting of a and F, UAV 2 is responsible for the fire-fighting of B and E, UAV 3 is responsible for the fire-fighting of D and G, UAV 4 is responsible for the fire-fighting of C, and UAV 5 is responsible for the fire-fighting of H, Each UAV has been used close to the maximum utility, and UAV resources have not caused waste and task overload. According to the fire-fighting task allocation results obtained by particle swarm optimization algorithm, the task allocation of each UAV is uneven. UAV 3 has too few tasks, while UAV 4 and UAV 5 have too heavy tasks. At the same time, the fire-fighting task allocation results obtained by particle swarm optimization algorithm cause the problem of multiple UAV task overload and repeated fire-fighting at task target points. Genetic algorithm also has a similar problem, and the degree of task overload and task repetition is more serious.



(a) Particle swarm optimization algorithm allocation results



(b) Genetic algorithm allocation results



(c) Algorithm allocation results in this paper

Figure 7. Comparison of fire extinguishing task allocation results of three types of algorithms.

3.5. Comparison with recent literature methods

In the past two years, some new research results have emerged in the multi-task allocation of UAV clusters. In order to further verify the performance of the method in this paper, it was compared with the method in literature [16]. The adaptability comparison of the two methods in reconnaissance task allocation is shown in Figure 8.

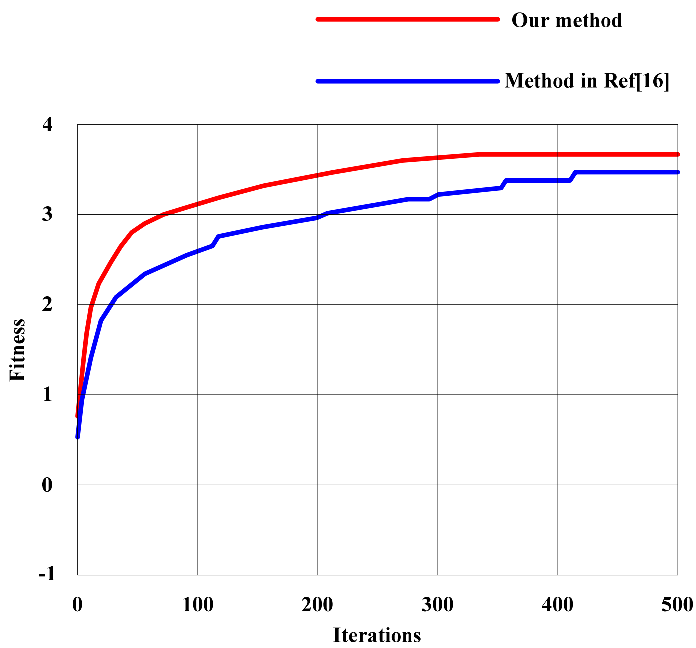


Figure 8. Comparison of fitness between two methods.

As can be seen from Figure 8, for the scenarios and tasks set in this experiment, the reconnaissance task allocation of the two methods has achieved relatively high fitness results. In contrast, the method in this paper has higher fitness and faster time to achieve stability of fitness.

4. Conclusions

UAV cluster is an effective means to solve the complex problems of unknown and unsafe environment. The task allocation of UAV individuals in the cluster is related to the expected completion of tasks and the efficiency of the cluster. Aiming at the problems of slow convergence speed, low convergence fitness level and easy to fall into local minimum of particle swarm optimization algorithm, a quantized particle swarm optimization algorithm (QPSO) is proposed for task allocation algorithm of UAV cluster. The quantized particle motion rule is built through Schrodinger equation, and Monte Carlo method is used to construct the update mechanism of quantized particle position. Five UAVs are used to build a cluster to complete eight groups of tasks. The experimental results show that QPSO algorithm shows faster convergence speed and higher fitness level in the three groups of experiments of reconnaissance, attack and fire suppression. The number of tasks assigned by each UAV in the cluster is reasonable and each UAV is used efficiently.

Acknowledgements

This project has been supported by Beijing nova program (Z201100006820107 & Z191100001119111), Beijing science and technology program (Z201100008120006) and national key research and development program (2020YFC1511600).

Conflict of interest

The authors declare there is no conflict of interest.

References

1. M. R. Khosravi, S. Samadi, Frame rate computing and aggregation measurement toward QoS/QoE in Video-SAR systems for UAV-borne real-time remote sensing, *J. Supercomput.*, **77** (2021), 14565–14582. https://doi.org/10.1007/s11227-021-03869-3
2. P. J. Zarco-Tejada, V. González-Dugo, J. Berni, Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera, *Remote Sens. Environ.*, **1** (2012), 322–337. https://doi.org/10.1016/j.rse.2011.10.007
3. H. Hamam, Energy efficient UAV flight path model for cluster head selection in next-generation wireless sensor networks, *Sensors*, **21** (2021), 606–615. https://doi.org/10.3390/s21248445
4. H. Wu, X. Tao, N. Zhang, X Shen, Cooperative UAV cluster-assisted terrestrial cellular networks for ubiquitous coverage, *IEEE J. Sel. Areas Commun.*, **36** (2018), 2045–2058. https://doi.org/10.1109/JSAC.2018.2864418
5. F. L. Duarte, R. C. De Lamare, C-RAN-type cluster-head-driven UAV relaying with recursive maximum minimum distance, *IEEE Commun. Lett.*, **24** (2020), 2623–2627. https://doi.org/10.1109/LCOMM.2020.3009845
6. C. He, Z. Xie, C. Tian, A QoE-oriented uplink allocation for multi-UAV video streaming, *Sensors*, **19** (2019), 3394–3408. https://doi.org/10.3390/s19153394
7. H. A. L. Thi, D. M. Nguyen, T. P. Dinh, Globally solving a nonlinear UAV task assignment problem by stochastic and deterministic optimization approaches, *Optim. Lett.*, **6** (2012), 315–329. https://doi.org/10.1007/s11590-010-0259-x
8. P. Ma, E. Lee, M. Tsuchiya, A task allocation model for distributed computing systems, *IEEE Trans. Comput.*, **31** (1982), 41–47. https://doi.org/10.1109/TC.1982.1675884
9. Y. Jiang, Y. Zhou, W. Wang, Task allocation for undependable multiagent systems in social networks, *IEEE Trans. Parallel Distrib. Syst.*, **24** (2013), 1671–1681. https://doi.org/10.1109/TPDS.2012.249
10. M. Theile, H. Bayerlein, R. Nai, D. Gesbert, M. Caccamo, UAV coverage path planning under varying power constraints using deep reinforcement learning, in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (2020), 1444–1449. https://doi.org/10.1109/IROS45743.2020.9340934
11. S. Yadav, R. Mohan, P. K. Yadav, Task allocation model for optimal system cost using fuzzy c-means clustering technique in distributed system, *Ing. Syst. D Inf.*, **25** (2020), 59–68. https://doi.org/10.18280/isi.250108

12. H. Kumar, I. Tyagi, Task allocation model based on hierarchical clustering and impact of different distance measures on the performance, *Int. J. Fuzzy Syst. Appl.*, **9** (2020), 105–133. https://doi.org/10.4018/IJFSA.2020100105
13. W. Fang, C. Wang, R. Zhao, Application of simulated annealing particle swarm optimization in complex three-dimensional path planning, in *Journal of Physics: Conference Series*, **1873** (2021), 012077.
14. M. Yan, H. Yuan, J. Xu, Y. Yu, L. Jin, Task allocation and route planning of multiple UAVs in a marine environment based on an improved particle swarm optimization algorithm, *EURASIP J. Adv. Signal Process.*, **2021** (2021), 1–23. https://doi.org/10.1186/s13634-021-00804-9
15. W. Zhang, W. Zhang, Efficient UAV localization based on modified particle swarm optimization, in *2022 IEEE International Conference on Communications Workshops (ICC Workshops)*, (2022), 1089–1094. https://doi.org/10.1109/ICCWorkshops53468.2022.9814686
16. L. Zhou, S. Leng, Q. Liu, Q. Wang, Intelligent UAV swarm cooperation for multiple targets tracking, *IEEE Internet Things J.*, **9** (2022), 743–754. https://doi.org/10.1109/JIOT.2021.3085673
17. M. Asim, W. K. Mashwani, S. B. Belhaouari, S. Hassan, A novel genetic trajectory planning algorithm with variable population size for multi-UAV-assisted mobile edge computing system, *IEEE Access*, **9** (2022), 125569–125579. https://doi.org/10.1109/ACCESS.2021.3111318
18. M. Asim, M. ELAffendi, A. A. El-Latif, Multi-IRS and Multi-UAV-Assisted MEC System for 5G/6G Networks: Efficient Joint Trajectory Optimization and Passive Beamforming Framework, *IEEE Trans. Intell. Transp. Syst.*, **9** (2022). https://doi.org/10.1109/TITS.2022.3178896