Efficient Joint Deployment of Multi-UAVs for Target Tracking

Jiashuai Wang[1], Lu Sun[1(✉)], Liangtian Wan[2], Jibin Zheng[3], and Xianpeng Wang[4]

[1] Institute of Information Science Technology, Dalian Maritime University, Dalian, China
sunlu@dlmu.edu.cn
[2] Key Laboratory for Ubiquitous Network and Service Software of Liaoning Province, School of Software, Dalian University of Technology, Dalian, China
wanliangtian@dlut.edu.cn
[3] National Laboratory of Radar Signal Processing, Xidian University, Xian, China
jbzheng@mail.xidian.edu.cn
[4] State Key Laboratory of Marine Resource Utilization in South China Sea and College of Information Science and Technology, Hainan University, Haikou, China

Abstract. Target tracking plays an important role in many real-world applications, such as in vegetation protection, disaster rescue, wildlife observation, etc. Multiple unmanned aerial vehicles (multi-UAVs) can provide effective services for target tracking through efficient joint deployment satisfying the system constraints. The constraints include the energy and no-fly zone constraint of each UAV, the communication distance and safe distance among multi-UAVs, the number of UAVs. As there exists no ready-made model that considers all the above constraints, meanwhile, the energy and no-fly zone restrict the deployment of multi-UAVs for target tracking. In this paper, we propose a model which considers no-fly zone and the energy constraint simultaneously for the joint deployment of multi-UAVs. The objective function is defined as minimizing the distance of each UAV and the threats of target so that it can deploy multi-UAVs reasonably. Second, we propose an improved Nondominated Sort Genetic Algorithm II (NSGAII) with new encoding and decoding mechanisms and the no-fly zone avoidance strategy which can improve the searching performance of joint deployment of multi-UAVs. Finally, we design a set of experiments and the experimental results demonstrate that our proposed algorithm can deploy multi-UAVs for target tracking efficiently compared with the state-of-the-arts methods.

Keywords: Multiple-UAVs · Target tracking · No-fly zone · NSGAII

1 Introduction

Target tracking is an important issue in many real-world applications and scenarios, such as vegetation protection, disaster rescue, wildlife observation [1].

V. C. M. Leung et al. (Eds.): Qshine 2023, LNICST 574, pp. 409–421, 2024.
https://doi.org/10.1007/978-3-031-65123-6_30

After observing and searching, the target with a particular value offers valuable information through tracking it. There are obstacles and devices threaten the safety of vegetation, disaster, wildlife, etc. Target tracking is critical to observe the status of target at any time and track in a period. In this paper, the dynamic environment and the no-fly zone are considered simultaneously.

Multiple unmanned aerial vehicles (Multi-UAVs) are employed widely, especially in the application of target tracking [5,9,17,29,36]. Multi-UAVs effectively track the targets with particular value and search all targets effectively, because of large scale UAVs. Communication equipment can help multi-UAVs perform tracking tasks [14]. In 2020, Azerbaijan *et al.* carried out precision strikes on important targets, personnel, and equipment in Armenia and achieved great results by multi-UAVs. However, the constraints in the real-world applications bring challenges to the deployment of multi-UAVs. The target tracking improves the complexity of tasks, and the no-fly zone restricts the movement of UAVs. The number of tasks handled by each single UAV is limited by the energy constraint of UAV. However, there exists no ready-made model that considers all the above constraints.

According to the existing work, the main joint deployment methods of target tracking focus on planning the route through the track and resource allocation. The trajectory planning fully considers the aerodynamic characteristics of the UAV to obtain multiple trajectories of multi-UAVs and selects the trajectory which meets our needs as the scheduling plan in those trajectories best [31,35,37]. The resource allocation methods regard UAVs as resource and find the most suitable task scheduling plan in solution space by the evaluation indicators for multi-UAVs with the help of objective function [2,25,34]. Task scheduling of multi-UAVs aims to maximize revenue under the premise of satisfying various constraints, rationally arranging tasks and limited task resources for UAVs, which is one of great significance for improving the efficiency of task execution and resource allocation. However, the current resource allocation algorithms are not suitable for this model. These existing algorithms cannot be used for this model directly. Thus, the main contributions of this paper are given as follows:

1) We propose a model which fully and simultaneously considers the energy and no-fly zone constraint of each UAV, and the communication distance and safe distance among multi-UAVs.
2) We propose a no-fly zone avoidance strategy to help multi-UAVs avoid no-fly zone while joint deployment.
3) We improve the NSGAII with a new encoding and decoding mechanisms, meanwhile, a no-fly zone avoidance strategy is enabled and considered simultaneously.

The rest paper is organized as follows: Sect. 2 reviews the existing related work corresponding to target tracking, joint deployment and multi-objective optimization algorithms. Section 3 constructs the system model of multi-UAVs joint deployment for target tracking. Section 4 describes our proposed improved NSGAII. Section 5 gives the simulation experimental setting and results. Section 6 comes to the conclusion and the future work.

2 Related Works

Researcher studied large-scale targets handling in dynamic environment [10,21,23]. Nevertheless, the physical structure of UAVs also restrict the efficiency when UAVs perform tasks in real-world applications [4,33]. Lanillos *et al.* studied the detection of missing targets, guiding the search of the targets effectively through expected observation information and continuously updating the observation information based on the rolling time domain. The method improved the probability of target discovery and the efficiency of targets detection greatly [7,15]. Steyer *et al.* used UAV sensor detection and analysis of the enemy aircraft's potential range of motion and based on Bayesian theory to update the motion probability map [19,24]. Wu *et al.* proposed an ant colony algorithm based on dynamic labor distribution [11,30]. The algorithm shown a high degree of self-organization, fast response and flexibility in uncertain environment. In order to solve the problem which is close to the real-world applications, this paper designs the algorithm structure to carry out the resource scheduling task for the target in the tracking environment.

Moreover, existing research studied the constraints for deployment of multi-UAVs in dynamic environment. Considering the constraints from UAVs, Lyu *et al.* considered the safe distance of the UAVs to avoid collision and obstacles designed flight attitude adjustment rules [18]. In order to reduce the constraints from a single UAV, Franco *et al.* calculated the flight energy consumption constraint according to the real UAV unit time power curve [6,12]. In order to reduce the constraints from the no-fly zone, Li *et al.* proposed a method which utilized the centripetal acceleration to avoid the no-fly zone [16]. Shen *et al.* proposed which the flight trajectory was divided into several parts, and UAVs can make decisions for the next segment when it was searched in front [22]. Tian *et al.* proposed a two-level dynamic alert zone in which UAV can enter the no-fly zone and wait for the no-fly zone transform fly zone in this model [27]. The methods mentioned above are summarised based on constraints from UAVs and real-world applications. However, these constraints are not considered in one model, simultaneously.

The joint deployment of UAVs is a critical step when utilizing the multi-UAVs to perform tasks for target tracking. Recently, the deployment algorithms based on swarm intelligence algorithm attracts researchers' attentions. Jin *et al.* designed a distributed ant colony algorithm based on ant communication and designed local, global, and pheromone update strategies after target discovery [8,13]. However, the ant colony algorithm is unsuitable for deployment of large-scale swarm UAVs. Some researchers focused on the planning algorithm based on route planning. Tahir *et al.* proposed a multi-agent trajectory planning method [26]. The trajectory planning problem was modeled as two coupled multi-agent stochastic games, whose equilibrium constituted the optimal trajectory. As the trajectory planning method was mostly offline, the performance of online problem is not perfect. Moreever, the planning algorithms based on the intelligent evolutionary algorithms are summarised. Wang *et al.* designed a genetic algorithm based on double-chromosome coding and multi-paragraph mutation [28]. The NSGAII algorithm was applied to joint deployment of swarm UAVs to improve task execution efficiency. Cheng *et al.* proposed an improved multi-objective genetic algorithm to solve the problem through deployment of multi-UAVs [3]. However, the performance of the NSGAII algorithm is limited in the actual task execution due to the general decoding and encoding mechanisms.

3 The Model of Multi-UAVs for Target Tracking

Multi-UAVs can provide effective services for target tracking through efficient joint deployment satisfying the system constraints. The constraints include the energy and no-fly zone constraint of each UAV, the communication distance and safe distance among multi-UAVs, the number of UAVs [32]. As there exists no ready-made model that considers all the above constraints, meanwhile, the energy and no-fly zone restrict the deployment of multi-UAVs for target tracking in dynamic environment. Therefore, we proposed a model that considers all constraints above simultaneously in this section.

3.1 Assumption

The assumptions are listed as follows:

A1. The flying height of the UAV is fixed, and the motion model of the UAV is simplified on a two-dimensional plane.
A2. The flight trajectory of the UAV is controlled by the coordinates of the targets. The flight path of the UAV is a straight line.
A3. The multi-UAVs are homogeneous. The tracking task requires multiple the cooperation of UAVs, and the recurring task requires UAVs to reconnaissance the mission target.

3.2 Mathematical Model

When UAV performs tasks, the flying distance of a single UAV restricts the deployment of multi-UAVs. Moreover, the flying distance of a single UAV is related to the efficiency of the tasks. While performing searching tasks, it is necessary to quickly detect the targets and improve mission completion reliability. In this paper, the flight distance of a single UAV and the threat of tracking targets are used as optimization indexes to improve the efficiency and reliability of search and tracking missions. The calculation formula for the flight distance and threat of each UAV is listed as follows:

$$\begin{cases} min\left(max\left\{D_i.....D_N\right\}\right) \\ min\left(R\left(track\right)\right), \quad i=1......N, \end{cases} \tag{1}$$

$$D_i = \sum_{n=1}^{N_i} \left|d_n\right|, \tag{2}$$

$$R\,(track) = \sum_{k=1}^{M_1} \int_0^{t_k} r\,(t)\,dt, \tag{3}$$

$$t_k = T_i^f + T_i^h, \tag{4}$$

$$T_i^f = \frac{D_i}{v_i}, \tag{5}$$

where N represents the number of UAVs participating in mission execution. $R()$ represents the risk (risk metric) generated by the tracking target and the recurring target. N_i represents the number of tasks performed by the i^{th} UAV. $|d_n|$ represents the flight distance from the completion of the previous mission to the current mission position. n represents the sequence number of the currently executing task. M_1 represents the number of tracking targets. t_k represents the time from when the tracking target appears to the target starts to be tracked. $r()$ represents an increasing risk function related to time. T_i^f represents the flight time of i^{th} UAV. T_i^h represents the handle time of i^{th} UAV.

3.3 The Structure of System Model

Evolutionary algorithm is an efficient method to handle large-scale tasks optimization problem. So, this paper proposes a model that uses evolutionary algorithm to deploy multi-UAVs. This model improve the efficiency of processing targets in real environment by deploy UAVs and tasks reasonably. The model consists of three parts in Fig. 1. The monitoring module is mainly responsible for monitoring the targets and return tasks information in real environment. The control module is responsible for generating the resource scheduling plan of the multi-UAVs with the improved NSGAII. In addition, the control module is responsible for the no-fly zone avoidance, which are added to the cluster drone scheduling plan. The actuator module is responsible for dispatching UAVs in accordance with the scheduling plan given by the control module. The no-fly zone avoidance are as follows.

3.4 No-fly Zone Avoidance Method

The shape of no-fly zone varies in previous works. In those shape of no-fly zone regular hexagon has outstanding performance of coverage, bigger geometric proportion and more geometric vertices that can be used in this avoidance method. So, the shape of the no-fly zone is a regular hexagon in this paper. In order to solve the restrictions of the no-fly zone, this paper introduces the method that uses intermediate points to avoid the no-fly zone. Intermediate point is the point on the edge of the no-fly zone. Adding it to the flying route of UAV can realize the avoidance of the no-fly zone.

A few definitions are proposed before introducing the detailed steps. Starting point (SP): the target with the early order will be executed among the two targets blocked by the no-fly zone. Terminal point (TP): the target with the latter order will be executed among the two targets blocked by the no-fly zone. Straight connection point (SCP): the ray from TP/SP to SCP without crossing the no-fly zone. All SCPs of SP are stored in straight connection point collect of SP (SCPCS).

All SCPs of TP are stored in straight connection point collect of TP (SCPCT). The intersection of SCPCS and SCPCT represented by ISCP. $D_{sa}$and D_{ta} are the distance from SP and TP to the closest vertices to the SP and TP of the no-fly zone. D_l is the side length of the regular hexagon. The following relationship determines the number of SCPs in SCPCS or SCPCT, if $D_{ta} \leq D_l$, the two points closest to TP among the vertices of the regular hexagon are selected in SCPCS, which are the vertices 3 and 4 shown in Fig. 2. If $D_{ta} \geq D_l$, the three points closest to TP among the vertices of the regular hexagon are selected in SCPCS, and which are the vertices 1, 2 and 6 shown in Fig. 3 (The same is for SP).

The steps used for avoiding the no-fly zone is listed as follows. First, we calculate the SCPCS and SCPCT of SP and TP according to the Euclidean distance formula. Second, we determine the intermediary point. If ISCP is empty, select suitable vertices on the regular hexagon as intermediate points. The avoidance route of UAV is shown by blue solid line in Fig 4. Finally, if ISCP is not empty, select suitable vertices in the ISCP as intermediate points. The avoidance route of UAV is shown by blue solid line in Fig. 5.

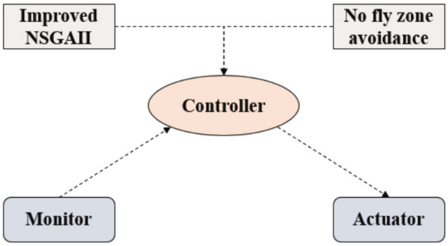


Fig. 1. The structure of system model.

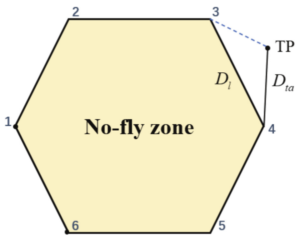


Fig. 2. The number of SCP is selected as SCPCS or SCPCT.

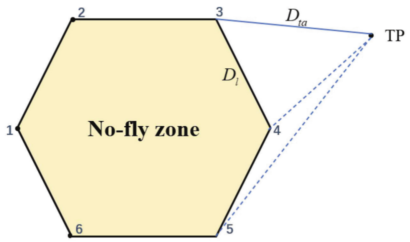


Fig. 3. The number of SCP is selected as SCPCS or SCPCT.

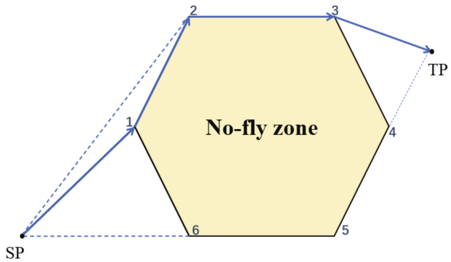


Fig. 4. The avoidance route of UAV when ISCP is empty. (1, 6 are the intermediary point of SP, 3, 4 are the intermediary point of TP).

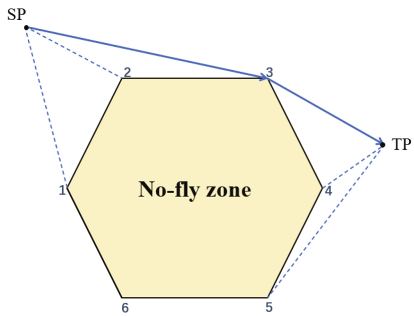


Fig. 5. The avoidance route of UAV when ISCP is not empty. (1, 2, 3 are the intermediary point of SP, 3, 4, 5 are the intermediary point of TP). (Color figure online)

4 Algorithm Description

4.1 The Procedure of Improved NSGAII

Algorithm 1. The procedure of improved NSGAII.

```
Input: N_max, P_m, N_1, N_2, N_3 N_A
Output: solutions with highest rank in R
    while iteration <N_2+1
        randomly generate population P
        for each individual i in P
            calculate the fitness F_i and non-dominated rank R_i of i
        end for
        select N_A individuals into archive P_0 according to R and F
    end while
    return P_0
    while iteration <N_max+1
        for each individual j in P_0
            calculate the fitness F_j and non-dominated rank R_j of j
        end for
        select N_1 individuals into P_1 according F_1 and R_1
        Crossover and mutation obtain P_2
        for each individual j in P_2
            if rand > P_m
                mutate individual j
            end if
        end for
        update population P_0
    end while
    return solutions with highest rank in R_1
```

NSGAII is an outstanding method for deploying multi-UAVs, and this superiority is limited by the constraints in the real environment, especially in the strength of search and diversity of solutions. In this paper, we propose a new method for encode and decode to improve the number of feasible solutions. And we add to a step to preprocesses the feasible solution in front of the structure of NSGAII. This step is parallel method of population generation to improve the diversity of solutions. The improved algorithm is shown in Algorithm 1 [20]. N_{max} represents the maximum times of generations for algorithm, P_m is the probability of the mutation, N_1, N_2 is constant, P_0, P_1, P_2 are population of individuals in different phase, N_A is the number of individuals for archive.

4.2 Population Initialization

Representation is basic part for the intelligent evolutionary algorithm. Representation is related with the diversity of population closely. A suitable representation can represent more potential solutions, and it increases the probability of finding an optimal solution. The classical direct representation is inefficient in the actual problem. This paper considers those problems fully and propose a new representation that adopts a co-evolution representation that considers the resource allocation of UAVs. This representation consists of two sections: the later section represents the sequence and sort of targets tracking, and the earlier section represents the sequence and sort of common targets. An illustration of a co-evolution representation is shown in Fig. 6.

In Fig. 6, we adopt a two-stage representation for the solution. First stage represents the deployment of UAVs for common targets, U_x represents the order of UAV for common target and N_c represents the number of common targets. Second stage represents the deployment of UAVs for special targets, U_s represents the order of UAV for special target and N_s represents the number of special [25].

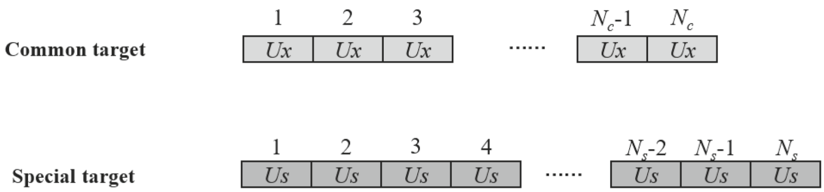


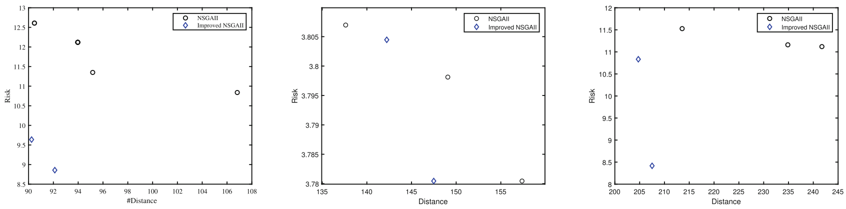
Fig. 6. Illustration of a co-evolution representation.

5 Numerical Experiments

5.1 The Performance of Different Scale of Targets

This section contrasts the difference between NSGAII and improved NSGAII with different scales of UAVs and targets in Fig. 7. The scales of UAVs and targets are 50 and 150 initially, and the scale of targets will increase to 300 and 500 in later experiments. In Fig. 7, those experiment indicate that the improved NSGAII have a better result. The reason is that NSGAII obtains potential solutions in a smaller space of solution, so we use a parallel style to generate solution, which can retain the potential solutions in a large space of solution.

In Fig. 7, the bule diamond represents the results of improved NSGAII and the black circle represents the results of the NSGAII. The horizontal axis represents the distance of a single UAV that completed tasks, and the horizontal vertical axis represents the risk that produced by targets with time increase. From Fig. 7, we can get conclusions that the bule one has a smaller numberical value than black one, espically in risk. It is important that has a small risk when UAVs perform tasks in real environment. So, the performance of improved NSGAII better than NSGAII in real environment target tracking.

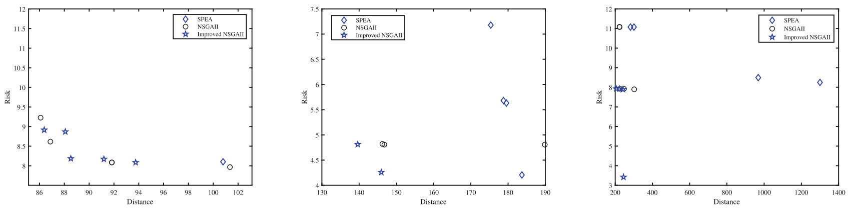


(a) (b) (c)

Fig. 7. Illustration of the results for NSGAII and improved NSGAII with different scale of targets ((a) represents the result for 150 targets, (b) represents the result for 300 targets, (c) represents the result for 500 targets).

5.2 The Confrontation of Different Evolution Algorithm with Improved NSGAII

This section contrasts the difference between other algorithm and improved NSGAII with different scales of UAVs and targets in Fig. 8. In Fig. 8 ,the blue pentagram represents the results of Improved NSGAII, the black circle represents the results of NSGAII, and the blue diamond represents the results of Strength Pareto Evolution Algorithm (SPEA). The experiment illustrate that improved NSGAII has a smaller risk and distance in every subexperiments than others. So, we conclude that improved NSGAII has a better performance than the NSGAII and SPEA. It can improve the efficiency of tasks in real environment.



(a) (b) (c)

Fig. 8. Illustration of the results for different evolution algorithm with different scale of targets ((a) represents the result for 150 targets, (b) represents the result for 300 targets, (c) represents the result for 500 targets). (Color figure online)

6 Conclusions

In this paper, we propose a model which considers no-fly zone and the energy constraint simultaneously for the joint deployment of multi-UAVs. Then, we propose an improved NSGAII with new encoding and decoding mechanisms and no-fly zone avoidance strategy which can improve the searching performance of joint deployment of multi-UAVs. Finally, we design a set of experiments and the simulation experiments verify the effectiveness of our improved NSGAII no-fly zone avoidance strategy. In the future work, we will focus on the joint deployment of multi-UAVs for target tracking in dynamic environment which includes target recurrence, online target tracking.

Acknowledgements. This work is supported by National Natural Science Foundation of China (62101088, 61801076, 61971336), National Natural Science Foundation of Liaoning Province (2022-MS-157), Radar Signal Processing National Defense Science and Technology Key Laboratory Fund (6142401200101), Fundamental Research Funds for the Central Universities (3132022230, DUT20JC29) and Dalian High-level Talent Innovation Support Plan No. 2019RQ024.

References

1. Alebele, Y., et al.: Estimation of crop yield from combined optical and sar imagery using gaussian kernel regression. IEEE J. Selected Topics Appl. Earth Observat. Remote Sens. **14**, 10520–10534 (2021)
2. Chen, K., Wang, Y., Zhao, J., Wang, X., Fei, Z.: Urllc-oriented joint power control and resource allocation in UAV-assisted networks. IEEE Internet Things J. **8**(12), 10103–10116 (2021)
3. Cheng, Y.F., Shao, W., Zhang, S.J., Li, Y.P.: An improved multi-objective genetic algorithm for large planar array thinning. IEEE Trans. Magn. **52**(3), 1–4 (2015)
4. Cui, J., Liu, Y., Nallanathan, A.: Multi-agent reinforcement learning-based resource allocation for UAV networks. IEEE Trans. Wirel. Commun. **19**(2), 729–743 (2019)
5. Das, A., Shirazipourazad, S., Hay, D., Sen, A.: Tracking of multiple targets using optimal number of UAVs. IEEE Trans. Aerosp. Electron. Syst. **55**(4), 1769–1784 (2018)
6. Di Franco, C., Buttazzo, G.: Coverage path planning for UAVs photogrammetry with energy and resolution constraints. J. Intell. Rob. Syst. **83**(3), 445–462 (2016)
7. Fan, H., Kucner, T.P., Magnusson, M., Li, T., Lilienthal, A.J.: A dual PHD filter for effective occupancy filtering in a highly dynamic environment. IEEE Trans. Intell. Transp. Syst. **19**(9), 2977–2993 (2017)
8. Gao, S., Wu, J., Ai, J.: Multi-UAV reconnaissance task allocation for heterogeneous targets using grouping ant colony optimization algorithm. Soft. Comput. **25**(10), 7155–7167 (2021)
9. Haoran, S., Faxing, L., Hangyu, W., Junfei, X.: Optimal observation configuration of UAVs based on angle and range measurements and cooperative target tracking in three-dimensional space. J. Syst. Eng. Electron. **31**(5), 996–1008 (2020)
10. Harikumar, K., Senthilnath, J., Sundaram, S.: Multi-UAV oxyrrhis marina-inspired search and dynamic formation control for forest firefighting. IEEE Trans. Autom. Sci. Eng. **16**(2), 863–873 (2018)
11. Husheng, W., Hao, L., Renbin, X.: A blockchain bee colony double inhibition labor division algorithm for spatio-temporal coupling task with application to uav swarm task allocation. J. Syst. Eng. Electron. **32**(5), 1180–1199 (2021)

12. Ji, J., Zhu, K., Yi, C., Niyato, D.: Energy consumption minimization in UAV-assisted mobile-edge computing systems: Joint resource allocation and trajectory design. IEEE Internet Things J. **8**(10), 8570–8584 (2020)
13. Jin, H., Ran, L.: A fair-rank ant colony algorithm in distributed mass storage system. Can. J. Electr. Comput. Eng. **38**(4), 338–345 (2015)
14. Khosravi, M.R., Samadi, S.: Mobile multimedia computing in cyber-physical surveillance services through UAV-borne video-SAR: a taxonomy of intelligent data processing for iomt-enabled radar sensor networks. Tsinghua Sci. Technol. **27**(2), 288–302 (2021)
15. Lanillos, P., Gan, S.K., Besada-Portas, E., Pajares, G., Sukkarieh, S.: Multi-UAV target search using decentralized gradient-based negotiation with expected observation. Inf. Sci. **282**, 92–110 (2014)
16. Li, R., Wei, Z., Yang, L., Ng, D.W.K., Yuan, J., An, J.: Resource allocation for secure multi-UAV communication systems with multi-eavesdropper. IEEE Trans. Commun. **68**(7), 4490–4506 (2020)
17. Liu, X., et al.: Transceiver design and multihop d2d for UAV IoT coverage in disasters. IEEE Internet Things J. **6**(2), 1803–1815 (2018)
18. Lyu, J., Wang, H.M.: Secure UAV random networks with minimum safety distance. IEEE Trans. Veh. Technol. **70**(3), 2856–2861 (2021)
19. Ru, C.J., Qi, X.M., Guan, X.N.: Distributed cooperative search control method of multiple UAVs for moving target. Int. J. Aeros. Eng. **2015** (2015)
20. dos Santos Coelho, L., Alotto, P.: Multiobjective electromagnetic optimization based on a nondominated sorting genetic approach with a chaotic crossover operator. IEEE Trans. Magn. **44**(6), 1078–1081 (2008)
21. Senthilnath, J., Omkar, S., Mani, V., Katti, A.R.: Cooperative communication of uav to perform multi-task using nature inspired techniques. In: 2013 IEEE Symposium on Computational Intelligence for Security and Defense Applications (CISDA), pp. 45–50. IEEE (2013)
22. Shen, L., Zhu, J.: On-line avoidance strategy with multiple no-fly zones. In: 2018 IEEE CSAA Guidance, Navigation and Control Conference (CGNCC), pp. 1–6. IEEE (2018)
23. Shima, T., Rasmussen, S.J., Sparks, A.G., Passino, K.M.: Multiple task assignments for cooperating uninhabited aerial vehicles using genetic algorithms. Comput. Oper. Res. **33**(11), 3252–3269 (2006)
24. Steyer, S., Tanzmeister, G., Wollherr, D.: Grid-based environment estimation using evidential mapping and particle tracking. IEEE Trans. Intell. Veh. **3**(3), 384–396 (2018)
25. Sun, L., Wan, L., Wang, X.: Learning-based resource allocation strategy for industrial IoT in UAV-enabled MEC systems. IEEE Trans. Ind. Inf. **17**(7), 5031–5040 (2020)
26. Tahir, H., Syed, M.N., Baroudi, U.: Heuristic approach for real-time multi-agent trajectory planning under uncertainty. IEEE Access **8**, 3812–3826 (2019)
27. Tian, G., Xiao, C., Liu, W.: Dynamic no-fly zone for drones. In: 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), pp. 761–766. IEEE (2019)
28. Wang, L., Singh, C.: Reliability-constrained optimum placement of reclosers and distributed generators in distribution networks using an ant colony system algorithm. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) **38**(6), 757–764 (2008)

29. Wang, S., Jiang, F., Zhang, B., Ma, R., Hao, Q.: Development of UAV-based target tracking and recognition systems. IEEE Trans. Intell. Transp. Syst. **21**(8), 3409–3422 (2019)
30. Wu, H., Li, H., Xiao, R., Liu, J.: Modeling and simulation of dynamic ant colony's labor division for task allocation of UAV swarm. Phys. A **491**, 127–141 (2018)
31. Xian, B., Wang, S., Yang, S.: An online trajectory planning approach for a quadrotor UAV with a slung payload. IEEE Trans. Ind. Electron. **67**(8), 6669–6678 (2019)
32. Yan, H., Bao, W., Zhu, X., Wang, J., Liu, L.: Data offloading enabled by heterogeneous UAVs for IoT applications under uncertain environments. IEEE Internet Things J. (2022)
33. Yu, J., Liu, X., Gao, Y., Shen, X.: 3d channel tracking for UAV-satellite communications in space-air-ground integrated networks. IEEE J. Sel. Areas Commun. **38**(12), 2810–2823 (2020)
34. Zeng, F., et al.: Resource allocation and trajectory optimization for QoE provisioning in energy-efficient UAV-enabled wireless networks. IEEE Trans. Veh. Technol. **69**(7), 7634–7647 (2020)
35. Zhao, C., Liu, J., Sheng, M., Teng, W., Zheng, Y., Li, J.: Multi-UAV trajectory planning for energy-efficient content coverage: a decentralized learning-based approach. IEEE J. Sel. Areas Commun. **39**(10), 3193–3207 (2021)
36. Zhao, N., et al.: UAV-assisted emergency networks in disasters. IEEE Wirel. Commun. **26**(1), 45–51 (2019)
37. Zhu, B., Bedeer, E., Nguyen, H.H., Barton, R., Henry, J.: UAV trajectory planning in wireless sensor networks for energy consumption minimization by deep reinforcement learning. IEEE Trans. Veh. Technol. **70**(9), 9540–9554 (2021)