Power-Aware Path Planning for Vehicle-Assisted Multi-UAVs in Mobile Crowd Sensing

Jie Xi, Liang Liu*, Mengqi Li, Xin Li and Jianfei Peng

College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics
Nanjing, China
Emails: {miracle, liangliu, mengqili, nuaalix, pengjf}@nuaa.edu.cn

***Abstract*—UAVs' high mobility and extensive coverage make them widely used as task performers in mobile crowd sensing (MCS). However, due to the limitation of the battery capacity, the flying distance of UAVs is limited, thus they cannot be continuously used in a wide area. In response to this problem, the ground vehicle can be used to transport, release, and recycle UAVs. Large-scale data collection can be achieved through the combined use of the ground vehicle and UAVs, where the route planning of vehicle-assisted UAVs is a key problem. The existing algorithms assume that the power of UAVs is unlimited or the charging time is negligible, which is impractical in real scenarios. In order to solve the above problems, we formalize a vehicle-assisted multi-UAVs path planning model based on the power of UAVs and propose an efficient and power-aware path planning algorithm for vehicle-assisted multi-UAVs(VMUPA). In VMUPA, we take genetic algorithm (GA) to plan flight paths of multi-UAVs under multiple constraints and obtain the power required at each parking spot. Then we optimize the driving route of the ground vehicle according to the remaining power of UAVs to minimize the overall time. Finally, performance evaluation is presented to demonstrate that VMUPA reduces the task completion time by 15% compared to existing algorithms in most cases.**

***Index Terms*—unmanned aerial vehicle, vehicle-assisted multi-UAVs, power-aware, route planning, mobile crowd sensing**

I. Introduction

Mobile crowd sensing(MCS) [1] usually uses individual mobile devices as basic perceptual units to complete large-scale and complex perception tasks [2], [3]. Besides, UAVs are becoming increasingly sophisticated. They have the characteristics of flexible operation, wide coverage, and have been widely used in agriculture, geological exploration, military, and other fields [4]–[10].

However, UAV-assisted mobile crowd sensing still faces several challenges: UAVs are limited by their battery and load capacity, which makes them unable to perform long-range or continuous tasks. Therefore, to expand the scope of UAVs' mission, ground vehicles can be introduced to assist them in the detection task by releasing and recycling them at designed parking spots. In addition, the ground vehicle acts as the mobile charging station for UAVs. After completing tasks, UAVs can be charged on the ground vehicle.

The core problem is how to plan the route of the vehicle and UAVs to minimize the time they take to complete the mission. However, most of the current research focused on optimizing the cargo delivery routes of vehicle-assisted UAV [11]. Furthermore, they did not consider the issue of charging power [12]. They assume that the power of the UAV is unlimited or the charging time is negligible, which is impractical in real scenarios. In fact, when the power of the UAV is not enough to complete the task, the UAV must be charged until the power reaches the take-off requirement.

To solve these problems, we propose an efficient and power-aware path planning algorithm for vehicle-assisted multi-UAVs(VMUPA). Firstly, instead of using only one UAV, we take advantage of multi-UAVs to sense the target area simultaneously. Secondly, we take the power and charging time of UAVs into account. After completing a mission, UAVs can be charged on the ground vehicle. And we plan the route of the ground vehicle according to the remaining power of UAVs. In general, our goal is to globally optimize the driving route of the vehicle and the flying paths of UAVs to minimize the task completion time.

To the best of our knowledge, this work is the first attempt to consider the issue of path planning for vehicle-assisted multi-UAVs which takes the power and charging time of UAVs into consideration.

The rest of the paper is structured as follows. Section II describes the system model; the proposed algorithm is presented in detail in Section III. Section IV introduces the simulation experiment, and we conclude the paper in Section V.

II. Problem Modeling

A. Problem Modeling

In our model, a large number of detection points are distributed in the target area and we need to visit these detection points to collect data. Each detection point only needs to be visited once by a UAV and the UAV can visit multiple detection points sequentially. However, due to the limitation of UAVs' battery capacity, the flying distance is limited. Therefore, a ground vehicle is introduced to assist UAVs to

This work is supported by the Aeronautical Science Foundation of China under Grant 20165515001, the National Natural Science Foundation of China under Grant No.61402225, State Key Laboratory for smart grid protection and operation control Foundation, and the Science and Technology Funds from National State Grid Ltd. (The Research on Key Technologies of Distributed Parallel Database Storage and Processing based on Big Data).

perform collection tasks. By releasing and recycling them on the ground vehicle, unnecessary flights can be avoided.

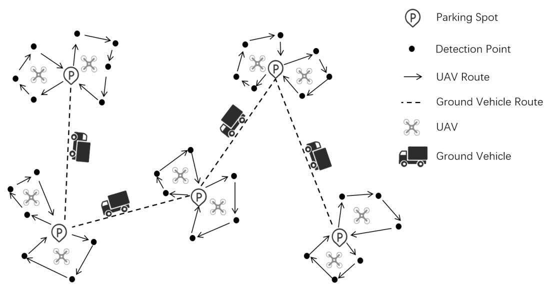


Fig. 1. System model.

As shown in Fig.1, with the help of the ground vehicle, UAVs can perform a wide range of collection tasks. The ground vehicle carries UAVs to the selected parking spot, then releases them to visit detection points sequentially and perform collection tasks. When the mission of a parking spot is completed, UAVs return to the ground vehicle to be charged. At the same time, the ground vehicle carries UAVs to the next parking spot to continue the data collection mission. The whole mission is finished when all detection points in the target area are visited.

III. Algorithm Design

A. Select Parking Spots

In this section, we select the most suitable parking spot for each detection point according to the distance between the detection point and the parking spot.

(1) Select Initial Parking Spots

We first calculate the distance between each detection point and the candidate parking spots same as VURA [15]. Each detection point chooses the nearest parking spot temporarily. We use $\theta_{p_i} = \left\langle c_1, c_2 \cdots c_{|\xi_{p_i}|} \right\rangle$ to represent detection points $c_1, c_2 \cdots c_{|\xi_{p_i}|}$ which select the parking spot $p_i (p_i \in f)$, and these detection points are sorted in descending order by the distance to p_i. $\theta^j_{p_i}$ represents the $j-th$ detection point in θ_{p_i}.

(2) Optimize the Selection of Parking Spots

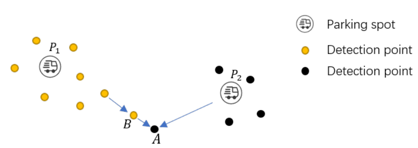


Fig. 2. How to choose parking spots

However, choosing the nearest parking spot does not mean that it is the best choice. The situation shown in Fig.2 may occur and we optimize the selection of parking spots for some detection points at the edge.

For the parking spot p_i with detection points θ_{p_i}, the steps to optimize the selection are as follows:

$a.$ Set $j = 1$.

$b.$ Find the nearest detection point c_x to $\theta^j_{p_i}$.

$c.$ Find the parking spot p_x which the detection point c_x belongs to. If c_x and p_i are different, it means that UAV needs more consumption to travel from p_i to $\theta^j_{p_i}$, hence $\theta^j_{p_i}$ reselect the parking spot p_x. Then set $j = j + 1$ and skip to step b; otherwise, skip to step d.

$d.$ Repeat steps above for all selected parking spots.

B. Plan the Flight Paths of UAVs

When the ground vehicle reaches the parking spot p_i, UAVs need to traverse the set of detection points ξ_{p_i}. We convert the flight paths of multiple UAVs into MTSP, which is a typical NP-hard problem. Therefore, we propose to use genetic algorithm [14] to solve it.

In contrast to the traditional genetic algorithm, we use multiple chromosomes instead of a single chromosome to initialize the population. In this way, we can separate the flight path of each UAV from each other, and reduce the size of the search space by eliminating redundant solutions. The experimental results are shown in section VI. The steps of the flight path planning based on genetic algorithm are listed as follows:

(1) Population Initialization

We use the flight path of the UAV as chromosome and it is defined as $\langle c_1, c_2, c_3, \cdots, c_j \rangle$, $c_j \in \xi_{p_i} (1 \le j \le |\xi_{p_i}|)$. We divide ξ_{p_i} into N_u chromosomes (corresponding to N_u UAVs) to form an individual.

(2) Fitness Calculation Function

For each individual in the population, the function calculates a fitness value fv which indicates the individual's performance and health. It can determine the individual's ranking in the population. Hence we define fv as the flight distance of all UAVs. Obviously, a smaller fv means that the individual is healthier and ranks higher in the group.

(3) Crossover and Mutation

In this paper, the crossover operation is used for multiple chromosomes in single individual. Parent chromosomes are selected within the individual and then chosen gene fragments are exchanged from the parent chromosomes to produce a new individual. Besides, the mutation operation is used on single chromosome of an individual.

(4) Selection Strategy

We choose the tournament selection strategy. K (K is the size of the tournament, the minimum is 2)individuals are randomly selected from the population, and the individual with the best fitness value is selected to enter the next generation population. Repeat this operation until the new population size reaches the size of original population.

C. Plan the Driving Route of the vehicle

After flight paths of UAVs are determined, we get the power needed P of UAVs to perform data collection tasks at each parking spot. In addition, we deduce the power charged Q of UAVs in the ground vehicle based on the distance between the parking spots. Therefore, we adopt the following heuristic algorithm to plan the driving route of the ground vehicle according to P and Q. We ensure that UAVs reach each parking spot with more power and perform data collection tasks faster. Besides, we reduce the coupling degree between the path planning of the ground vehicle and the charging time of UAVs at parking spots through the heuristic strategy, hence both of them can be optimized independently.

The steps to construct the route of the ground vehicle are as follows:

(1) Define Initial Candidate Solution

We propose a greedy algorithm to plan a path R_v with the shortest driving time between the parking spots. We ensure the minimum driving time first and then optimize the driving route. The pseudo-code for finding a candidate solution is shown in algorithm 1.

Algorithm 1 Find The Candidate Solution

Input: The set of selected parking spots f
Output: The driving route of the ground vehicle R_v

```
Dis(R_v^i, R_v^j) ← The distance between parking spot R_v^i and R_v^j
Set f[1] as the starting spot
R_v = {f[1]}
f ← f \ R_v
for i = 2 → |f| do
    Find the closest parking spot f_j to R_v^i
    R_v = R_v ∪ f_j
end for
Achieve the driving route of the ground vehicle, R_v
```

(2) Optimize the Candidate Solution

In this section, we optimize the candidate solution and the steps of optimizing the candidate solution are as follows:

a. Set $i = 1$.

b. Find the predecessor parking spot p_x of H_i. p_x has a set of candidate parking spots S, which includes all the next parking spots that can be reached by the ground vehicle.

c. Traverse S, exchange the traversed candidate parking spot with H_i to generate new routes.

d. Calculate the time cost of the new routes generated by step c. Choose the route with the shortest time cost and update the sequence H of the new route at the same time.

e. Set $i = i + 1$ and repeat steps above until the time cost of the new route no longer changes.

The pseudo-code for optimizing the candidate solution is shown in algorithm 2. And the experimental results show that the final result is the optimal solution in most cases.

IV. Experimental Simulation

A significant amount of experiments have been conducted to assess the performance of VMUPA. To evaluate the efficiency of VMUPA, we compare it with two algorithms: enumeration algorithm and VURA. We paid special attention to two performance metrics. The first is the time cost of the solution. It is defined by the total time of completing the whole data collection task. The second metric is the travel distance of the ground vehicle. The lower the travel distance, the lower the system cost [15].

Algorithm 2 Optimize The Candidate Solution

Input: The candidate solution R_v
Output: The optimized solution R_{op}

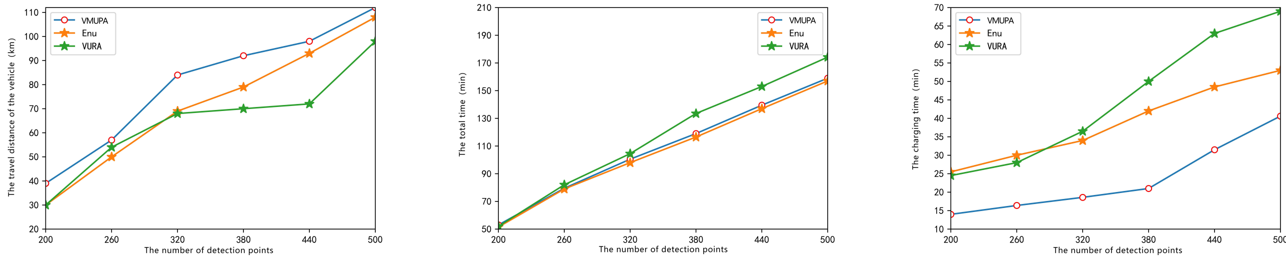
```
function OPTIMIZETHECANDIDATESOLUTION(i, R_v)
    T ← The time consumption of R_v
    Find the parking spot P_{R_v}^i
    for n = 1 → H.length do
        r ← Exchange H(n) and P_{R_v}^i
        t ← The time consumption of r
        if t < T then
            T ← t
            R_op ← r
            H_new ← update the sequence H
        else
            R_v ← Exchange H(n) and P_{R_v}^i
        end if
    end for
end function
```

In our experiments, several detection points are randomly generated in the 150 unit * 150 unit area, of which 1 unit represents 1 km. A vehicle with several identical UAVs is employed to visit detection points in the target region. The initial power of each UAV is 100 % and the speed of the vehicle and each UAV are set as 3m/s and 1m/s, respectively.

Fig.3(a)–(c) show the impact of the number of detection points on different algorithms. It can be seen from Fig.3 (a) that the distance traveled by the ground vehicle is positively related to the number of detection points. Still, VURA maintains the shortest driving distance of the ground vehicle in most cases, which is related to the conversion of the vehicle driving problem into TSP. Although the vehicle driving distance of VMUPA is slightly larger than that of VURA and the enumeration algorithm, the gap is decreasing. It can be seen from Fig.3 (b) that VMUPA is significantly better than VURA in terms of the total time to complete the task, especially when the number of detection points is large. And the solution sought by VMUPA is most likely to be the optimal solution. Fig.3 (c) shows that the solution sought by VMUPA has the shortest charging time at parking spots, while the solution obtained by VURA has the longest time for charging.

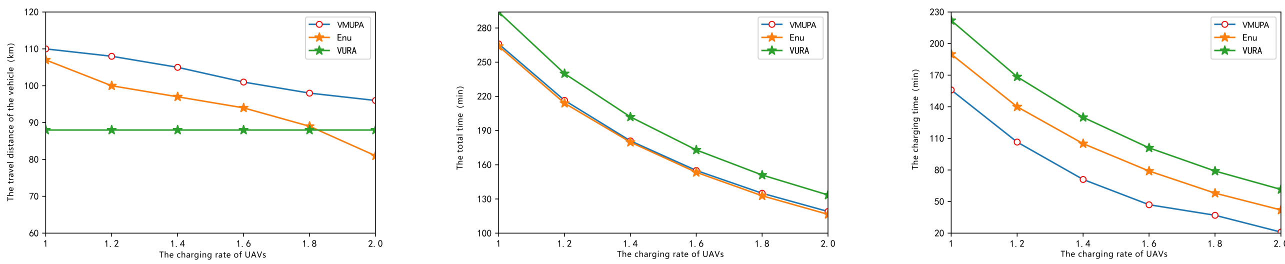
Fig.4(a)-(c) show the effect of the charging rate on different algorithms in detail. Fig.4 (a) shows that with the increase of the charging rate, the driving distance of the ground vehicle is decreasing. Besides, the increase in the charging rate improves the efficiency of the data collection task, and the total time of completing the entire task is correspondingly reduced. Nevertheless, the total time of the solution obtained by VURA is still much higher than that of VMUPA, and the solution obtained by VMUPA is very close to the optimal solution. Moreover, UAVs charging time of the solution obtained by VMUPA is much shorter than the other two algorithms.

Fig.5(a)-(b) show the influence of the number of UAVs on different algorithms in detail. As the number of UAVs increases, the total time gradually decreases. However, the



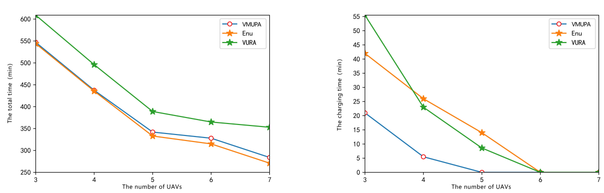
(a) The travel distance of the vehicle (b) The total time (c) The charging time

Fig. 3. Results when varying the number of detection points.



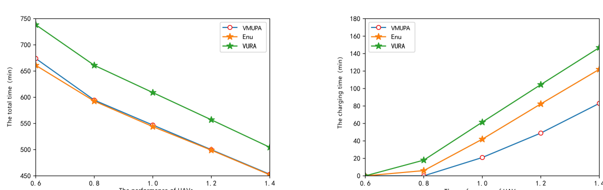
(a) The travel distance of the vehicle (b) The total time (c) The charging time

Fig. 4. Results when varying the charging rate.



(a) The total time (b) The charging time

Fig. 5. Results when varying the number of UAVs.



(a) The total time (b) The charging time

Fig. 6. Results when varying the performance of UAVs.

solution calculated by VURA still longer than that of VMUPA. At the same time, with the increase in the number of UAVs, the time of UAVs to be charged at the parking spot will be greatly reduced until it is unnecessary to do that.

Fig.6(a)-(b) detail the impact of UAV performance on different algorithms. It can be seen from Fig.6 (a) that under the same mission environment, the better the performance of the UAV, the shorter the time to complete the mission. However, the solution VURA seeks still takes more time than that of VMUPA. In addition, with the improvement of UAVs performance, the charging time of UAVs at parking spots has also increased among the schemes obtained by the three algorithms, but the scheme obtained by VMUPA always keeps the lowest value.

In summary, the solution sought by VMUPA always keeps the lowest time consumption and reduced by 15% compared to the solution sought by VURA in most cases, but in terms of the distance traveled by the vehicle, it is slightly larger than the solution sought by the other two comparison algorithms. Hence, VMUPA has dramatically improved the efficiency of completing tasks at the expense of some system cost; As we all know, MCS prefers real-time data, for UAVs' owner, the faster the mission is completed, the more economic benefits they can obtain. Therefore, the solution obtained by VMUPA can perfectly meet the needs of UAVs' owner.

V. Conclusion

In this paper, we propose an efficient and power-aware path planning algorithm for vehicle-assisted multi-UAVs(VMUPA). To the best of our knowledge, we are the first to take the charging time of UAVs into consideration. In VMUPA, we first select appropriate parking spots for detection points in the target area; then use GA to plan flight paths of UAVs; finally, we optimize the route of the vehicle to minimize the overall task completion time. The simulation results show that VMUPA outperforms the existing algorithms in terms of optimizing the time cost of the data collection task in most cases.

References

[1] Ma, Huadong, et al. “Opportunities in Mobile Crowd Sensing.” IEEE Communications Magazine, vol. 52, no. 8, 2014, pp. 29–35.

[2] Al-Muqarm A M A , Rabee F . IoT Technologies for Mobile Crowd Sensing in Smart Cities[J]. Journal of Communications, 2019, 14:745-757.

[3] Z. Zhou, J. Feng, B. Ai and M. Guizani, ”Energy-Efficient Mobile Crowd Sensing Based on Unmanned Aerial Vehicles,” 2018 IEEE Global Communications Conference (GLOBECOM), Abu Dhabi, United Arab Emirates, 2018, pp. 1-6, doi: 10.1109/GLOCOM.2018.8647849.

[4] Yang, Yuzhe, et al. “Real-Time Profiling of Fine-Grained Air Quality Index Distribution Using UAV Sensing.” IEEE Internet of Things Journal, vol. 5, no. 1, 2018, pp. 186–198.

[5] Wu, Yuanwei, et al. “Vision-Based Real-Time Aerial Object Localization and Tracking for UAV Sensing System.” IEEE Access, vol. 5, 2017, pp. 23969–23978.

[6] Feng, Quanlong, et al. “UAV Remote Sensing for Urban Vegetation Mapping Using Random Forest and Texture Analysis.” Remote Sensing, vol. 7, no. 1, 2015, pp. 1074–1094.

[7] Fan Ouyang, Hui Cheng, Yubin Lan, Yali Zhang, Xuanchun Yin, Jie Hu, Xiaodong Peng, Guobin Wang, Shengde Chen,Automatic delivery and recovery system of Wireless Sensor Networks (WSN) nodes based on UAV for agricultural applications,Computers and Electronics in Agriculture,Volume 162,2019,Pages 31-43,ISSN 0168-1699.

[8] L. Negash, H. Kim and H. Choi, ”Emerging UAV Applications in Agriculture,” 2019 7th International Conference on Robot Intelligence Technology and Applications (RiTA), Daejeon, Korea (South), 2019, pp. 254-257, doi: 10.1109/RITAPP.2019.8932853.

[9] Guerra, E.; Munguía, R.; Grau, A. UAV Visual and Laser Sensors Fusion for Detection and Positioning in Industrial Applications. Sensors 2018, 18, 2071.

[10] B. Wang, Y. Sun, D. Liu, H. M. Nguyen and T. Q. Duong, ”Social-Aware UAV-Assisted Mobile Crowd Sensing in Stochastic and Dynamic Environments for Disaster Relief Networks,” in IEEE Transactions on Vehicular Technology, vol. 69, no. 1, pp. 1070-1074, Jan. 2020, doi: 10.1109/TVT.2019.2949634.

[11] Ferrandez, Sergio Mourelo, et al. “Optimization of a Truck-Drone in Tandem Delivery Network Using k-Means and Genetic Algorithm.” Journal of Industrial Engineering and Management, vol. 9, no. 2, 2016, pp. 374–388.

[12] K. Peng et al., ”Wide-Area Vehicle-Drone Cooperative Sensing: Opportunities and Approaches,” in IEEE Access, vol. 7, pp. 1818-1828, 2019, doi: 10.1109/ACCESS.2018.2886172.

[13] Zhou, Zhenyu, et al. “When Mobile Crowd Sensing Meets UAV: Energy-Efficient Task Assignment and Route Planning.” IEEE Transactions on Communications, vol. 66, no. 11, 2018, pp. 5526–5538.

[14] Király, András, and János Abonyi. A Novel Approach to Solve Multiple Traveling Salesmen Problem by Genetic Algorithm. 2010, pp. 141–151.

[15] Hu, Menglan, et al. “Joint Routing and Scheduling for Vehicle-Assisted Multidrone Surveillance.” IEEE Internet of Things Journal, vol. 6, no. 2, 2019, pp. 1781–1790.

[16] Hu, Menglan, et al. “On the Joint Design of Routing and Scheduling for Vehicle-Assisted Multi-UAV Inspection.” Future Generation Computer Systems, vol. 94, 2019, pp. 214–223.