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Secure Multi-UAV Collaborative Task Allocation

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ABSTRACT Unmanned aerial vehicle technology has made great progress in the past and is widely used in many fields. However, they are unable to meet large-scale and complex missions with a limited energy reserve. Only multiple unmanned aerial vehicles (multi-UAV) work together to better cope with this problem and have been extensively studied. In this paper, a new systematic framework is proposed to solve the problem of multi-UAV collaborative task allocation. It is formulated as a combinatorial optimization problem and solved by the improved clustering algorithm. The purpose is to enable multi-UAV to complete tasks with lower energy consumption. As the number of UAVs rises, it also appears the flight safety issues such as collisions among the UAVs, an improved multi-UAV collision-resistant method based on the improved artificial potential field is proposed. Besides, the UAVs connected with the internet are vulnerable to the various type of network attacks, a method based on the intrusion detection system is proposed to resist the network attack during multi-UAV mission execution. We have also proposed an improved method to improve the accuracy of task allocation further. In addition, an online real-time path planning is proposed to enhance the robustness of multi-UAV to cope with sudden problems. Finally, the numerical simulations and real physical flying experiments showed that the proposed method could provide a viable solution for multi-UAV task allocation; moreover, compared with other task allocation methods, our method has great performance.

INDEX TERMS Multi-UAV, task allocation, collusion-resistant, secure communication, intrusion detection system, clustering algorithm.

I. INTRODUCTION

The UAV technology has developed rapidly in recent years, expanding from the past military applications to the civilian sector. The UAVs can replace the manned vehicles to execute a variety of complex tasks. With the advantages of the UAVs, it is widely used in security patrol [1], regional monitoring, target search [2], topographic mapping [3], mineral exploration [4] and agricultural production [5], etc. Although the UAVs also exposes many issues, mainly contain limited energy reserve, the limit of commination distance, which cannot perform the long-time and large-scale mission. The multi-UAV are formed as a cluster and work collaborative to complete missions effectively and quickly. The problem of multi-UAV collaborative task allocation is to arrange some UAVs to perform the tasks consists of given target waypoints in a shorter decision time, the purpose is to minimal system cost efficiently.

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When the multi-UAV are performing tasks, considering not only the benefits of single one, but also the overall benefits of the system. It is a complex combinatorial optimization problem with a variety of qualifications, considering the size of the mission, the flight energy reserve of the UAV, and the communication distance limit [6]. In real environment, it is difficult to describe this mathematical model accurately, especially the uncertainties from the external environment.

Importantly, the task-allocation problem is an NP-hard problem [7]. Therefore, the size of the problem (the number of waypoints, the number of missions, and the number of UAVs in the cluster) will affect the solution to the problem. The density of the UAVs in cluster determines its ability to solve problems. With the increasing of multi-UAV cluster density, the collision possibility [8], [9] is also increasing. In addition, when the number of UAVs is large, they are vulnerable to the network attack [10], [11]. The UAVs involve numerous public safety issues as well as privacy protection, they should meet the security demands such as privacy, confidentiality, integrity, and non-repudiation to provide secured communications against attackers, and malicious nodes. How to distribute a series of mission points to multi-UAV in a short period to maximize the total flight efficiency of the UAV system, under the guarantee of collision-resistant and the secured communications between the UAVs in cluster. In order to solve this problem, we try to find a system solution framework that can respond to uncertain environment and complex tasks.

In this paper, we propose a combined optimization model for collaborative task assignment in the actual execution of multi UAVs. Then we proposed a novel method based on improved artificial potential field to solve the problem of collision-resistant among UAVs as well as the method to resist network attack. Then we use the number of UAVs in the cluster as the number of subtasks. With the improved clustering algorithm, all the waypoints are divided according to the Euclidean distance between the waypoints, so that the tasks are equally distributed to the UAVs. Finally, in order to deal with the uncertain environment in the flying, we introduce the robustness theory and task online re-planning scheme should be this problem. The main contributions of this paper are as follows:

1) We propose the method to collision-resistant as well as resisting network attack for the flight safety of multi-UAV.
2) We propose a solution framework for the task allocation problem based on clustering algorithm and real-time online path planning method for the sudden problems.
3) We build a real experimental platform, and conduct the actual flight and simulation experiments proved the effectiveness of our algorithm.

The organization structure of this paper are as follows: the related issues are discussed detailedly in Section II. In Section III, we introduce the mathematical model and the problem formulation. In Section IV, we proposed the method to flight safety of multi-UAV. The framework of task allocation algorithm is proposed in Section V. In Section VI, we proposed the real-time online path planning under sudden task allocation. In Section VII, serval simulations conducted to verify our algorithm. Finally, further discussions and conclusions are proposed in Section VIII.

II. RELATED WORK

The problem of multi-UAV task allocation has been studied extensively. It mainly includes the basic mathematics model, solving algorithms and the handling of sudden problems.

A. MATHEMATICS MODEL

For the basic mathematical models of multi-UAV task allocation, varieties of models have emerged. Forsmo *et al.* [12] solved this problem by the mixed integer linear programming model (MILP). Kendall and Phillip used a network flow optimization model (NFO) [13], proposed a method to task allocation for drones in a cluster. Peng *et al.* [14] proposed a multi intelligent agent-based systems to task allocation. In addition, Alighanbari and How [15] attributed this problem to a Dynamic Programming (DP) problem, which is more tractable than the previous MILP solution method.

In recent years, with the development of interdisciplinary studies, some research methods in other fields have been applied to solve this problem. For example, Karaman *et al.* [16] build a model of this problem by the Process Algebra. The authors firmly grasp the time-sequence of these tasks with composition to express all actions of the multi-UAV. Similarly, Karaman and Frazzoli [17] introduced the linear temporal logic language to represent this problem and then apply it into MILP formulations.

B. SOLVING ALGORITHMS

In term of the solving algorithm, there is no perfect way to solve the NP-hard problem in present stage. Even though, it is possible to be solved in small-scale and medium-scale situations, the solving methods can be divided into centralized and decentralized. For the centralized method: Shima *et al.* [18] proposed a method on multi-agent to multi-task allocation problem by the genetic algorithm. Alighanbari *et al.* [19] introduce a MILP model to solve the task allocation problem by the Tabu Search algorithm. Zhu and Tang [20] introduced the method to task allocation by the particle optimization algorithm. Besides; tree search algorithm, the ant colony algorithm and state-space best-first search algorithm are also the centralized methods [21]–[23]. Most of these methods are global optimization algorithms that are very helpful in solving the NP-hard problems. The previous work of the distributed algorithms is significantly fewer than the ones of the centralized algorithms [24], [25]. The main advantage of the distributed algorithm to improve the robustness of multi-UAV task allocation. While multi-UAV are working cooperatively, others can re-allocate the task by the distributed algorithm immediately even if one of them cannot work well to ensure that the whole multi-UAV system can still work successfully. Even though, the distributed method is seldom ensuring the result optimization of the results.

When the UAVs in the cluster are executing tasks together in the Three-dimensional space, if the distance between the UAVs is shorter than the safe radius, the collision will occur. So the collision possibility is mainly determined by the relative position between the UAVs. Fraichard and Asama proposed Deterministic methods including the construction of regions of inevitable collision [26]. Du Toit and Burdick [27] proposed a method ignoring the uncertainty associated with the sensed obstacle, and proposed an approximation and its validity to enforce the result of collision chance constraints. Zhou *et al.* proposed a method that use a virtual rigid body abstraction, the collision are automatically avoided within the swarm of UAVs and between the UAVs and the obstacles [28]. Zhao Yue Zhang and Jing Zhang focused on the risk of conflict between manned and unmanned aerial vehicles and carry out the risk assessment experiment of unmanned aerial vehicle (UAV) in non-isolated airspace conflict. But the automatic avoidance system of UAV will increase [29].

The sudden problem of multi-UAV task allocation should be considered seriously, it concludes: the failure of UAV, changed environment, waypoints added in flight. Enhancing the robustness is a better method to establish the model, aiming to get an optimal result that can meet sorts of constraints in any situation even in the worst case. There are some frameworks for the robust optimization theory [28], [30]–[32]. If a new waypoint need to be add to the whole task [33], and the single task cannot be finished due to the commination problem of UAVs task re-allocation in real time that can ensure the effectiveness.

Compared with different model of multi-UAV task allocation, the model proposed in this paper is classical MILP model. In addition, we introduce the distributed algorithm that can improve the robustness of whole systems, and ensure the task re-allocation while a new waypoint added in real time.

III. PROBLEM DESCRIPTION AND FORMULATION

A. PROBLEM DESCRIPTION

There are N_t waypoints needed to be visited by UAV in a soon time, a UAV cannot meet the demands due to the limit of flight-distance. The problem proposed in this paper is assigning N_t waypoints to N_v UAV to finish the task with lower cost, where $N_v < N_t$ and $t, v \in (1, 2, 3 \ldots)$. The cost contains two parts: the flight-path length the time cost of task-allocation. For the first problem. By the mirror representation of the waypoints [14]. The method in this paper is that transform one waypoint multi tasks problem to one waypoint-one task problem, then the multi-UAV task allocation problem is defined as a multi Traveling Salesmen Problem (m-TSP). And then it can be formulated by a complete digraph $G = (V, E)$, where vertex set $V \in (1, 2, 3 \cdots)$ numbers the starting points of the UAV and the mirrored waypoint points; and each edge in $t, j \in E$ represents the shortest flying path between i waypoint and j waypoint (named city in m-TSP), where $i \neq j$. For the rotor UAV, the shortest path is the straight line of two waypoints. The m-TSP is also a NP-hard problem, so the main problem is that divided the total waypoint into N_s, $s \in (1, 2, 3 \cdots)$ tasks where $N_s < N_v$, then the m-TSP problem is formulated as N_s-TSP problem.

B. PROBLEM FORMULATION

The multi UAVs task allocation problem can be formulated as a combinatorial optimization problem:

$$\min \sum\nolimits_{s=1}^{N_s} \sum\nolimits_{t=1}^{N_t^s} \sum\nolimits_{v=1}^{N_v} P_s^k L_{i,j}^k X_{i,j}^k C_s^k \tag{1}$$

$$C_s = \sum\nolimits_{t=1}^{m} P_{i,j}^k L_{i,j}^k X_{i,j}^k \tag{2}$$

$$\sum\nolimits_{j=1}^{N_t} \sum\nolimits_{k=1}^{N_v} X_{i,j}^k = 1, \quad \forall j$$

$$\sum\nolimits_{t=1}^{N_t} \sum\nolimits_{k=1}^{N_v} X_{i,j}^k = 1, \quad \forall i \tag{3}$$

$$\sum\nolimits_{t=1}^{N_t} \sum\nolimits_{k=1}^{N_v} L_{i,j}^k < \sum\nolimits_{k=1}^{N_v} L_{\lim}^k, \quad \forall k \tag{4}$$

where $X_{i,j}^k$ is a 0-1 decision variable, which means that the k UAV flies from the i-th waypoint to the j-th waypoint. The N_t^s means that the s task consists of m waypoints where $m < N_t$. The $count(C_s)$ means the number of waypoint in the s-th task. The $L_{i,j}^k$ represents the length of the shortest path of k-th UAV flies from the i waypoint to the j waypoint. The P_s^k represents the succeed rate of whether the k-th UAV have enough energy storage metrics to receive the s task, due to the remind energy of current UAV. The L_{lim}^k means the maximum flying distance of k-th UAV with the limit energy.

The objective function (1) minimizes the weighted cost, which concludes three main components: succeed rates, flying length and the waypoint sequence of waypoint. Their computing details will be illustrated further in the section IIIC. For $\forall i, j \in (1.2.3 \ldots, N_t)$ and $\forall k \in (1.2.3 \ldots, N_k)$, when the UAV is flying between the waypoints, there are constraints are as follows: All the waypoints will be visited ensured by the constraint (3), which is the original constraint of the m-TSP problem. Each UAV must land off the waypoint where it takes off. The constraint (5) means that the sum length of N_k UAV flight distance is longer than the sum optimal path length of N_s task. According to this model, its variable dimension is $N_s \times N_t \times N_t^2$, with the increase of N_s N_v and N_t, this problem will be more complicated.

C. COMPUTING DETAILS

From the part B, the shortest feasible path L_{ij} can be computed by the coordinate of the i-th waypoint to the j-th waypoint by the Euclidian Distance methods. We assume V_k is the nominal velocity of the k-th UAV, then the $t_{i,j}^k$ is the flying time of the k-th UAV flies from i waypoint to j waypoint as follows:

$$L_{ij} = \sqrt{\sum\nolimits_{k=1}^{n} \left(x_i^k - x_j^k\right)^2} \tag{5}$$

$$t_{i,j}^k = \frac{L_{i,j}^k}{V_k} \tag{6}$$

In (1), the total cost of the multi-UAV depends on N_s task and the optional path. This problem is divided into two parts: allocating N_i waypoint to N_s task, path planning. We firstly allocate N_t waypoints into N_s lists, each list consists of N_m waypoints, where $m = count(C_s)$. The N_0 waypoint is the point where the UAVs take off. In addition, they only can land

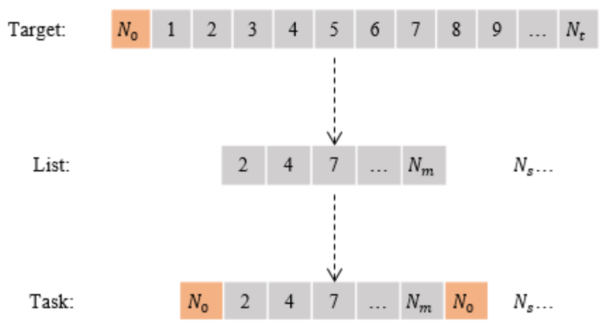

FIGURE 1. Subtask distributing process.

off at the same waypoint. Then we should append N_0 to the s list as the first point and the last point. Finally, the s task is boiled up by s list and two waypoint this method can be descripted as Fig.1.

The N_t waypoints are evenly distributed to N_s task. Then we allocate s-th task to the k-th UAV. Before the UAV flyting form the i-th waypoint to j-th waypoint, We sort the waypoints to find the best order to find the best path to reduce the flying distance, then the UAV take off and flying by the waypoint sequence, finally arrive and land at the N_0.

IV. MULTI-UAV FLIGHT SAFETY

A. METHOD TO COLLISION-RESISTANT

The UAVs in the cluster can fly in the Three-dimensional space, calculating the collision possibility is the premise of collision-resistant effectively. We assume that the UAVs are moving linearly so that we can the UAVs move in uniform linear motion, and their flying velocity can be measured. We assume that the distance of two UAVs is shorter than the safety radius then the UAVs will collide or have already collided. So the collision possibility is calculated by the distance between UAVs.

The collision possibility is an important standard to guarantee the flight safety among the UAVs and offer an important basis to multi-UAV task allocation. In order to handle data and analyze problems more obviously, we have assumed that the UAVs shape is considered as a particle. And once the UAVs meet, the process is regarded as static, and assumed that the UAVs have a linear velocity.

Calculating the collision possibility, the safety radius is the basic element for the collision judgement. Assuming that there are two UAVs are flying in the nearby apace descripted by Fig.2.

The coordinates of each UAV can be transferred from the onboard-computer to the mobile station in real-time. The $C_i\, \forall i \in (1.2.3\ldots)$ represents the coordinates include latitude, longitude, and altitude. Considering any two UAVs i-th and j-th. In addition, the velocity of k-th UAV is represented as V_k. The R_k represents the safety radius of k-th UAV. The a_k represents the accelerate velocity of k-th UAV. The programing time on calculating the relative position by the onboard-computer and the commutate lateness is seen as t.

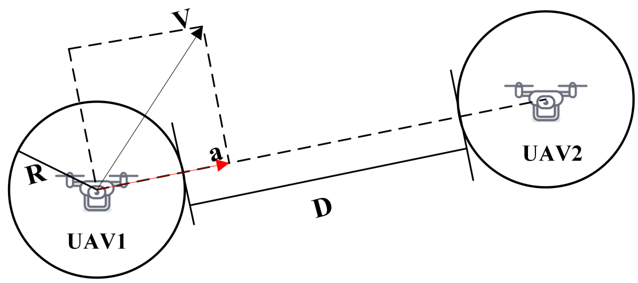

FIGURE 2. The safety radius and distance between UAVs.

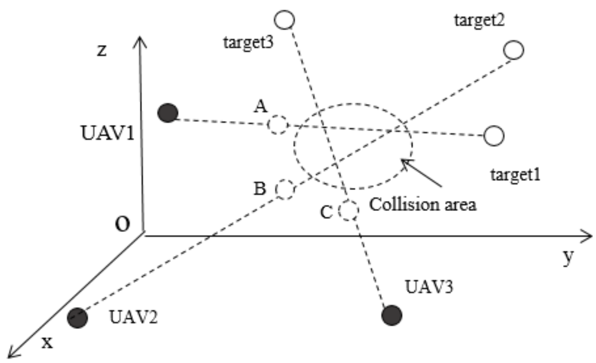

FIGURE 3. Multi UAVs fly by the path with collision risks.

Given that the C_i and C_j, calculated by (6), we can get the distance $C_{i,j}$ between i-th UAV and j-th UAV.

$$R_k = V_k t + \frac{V_k^2}{2a_k} \tag{7}$$

$$D_{i,j} = L_{i,j} - \sum\nolimits_{k=i}^{k=j} R_k \tag{8}$$

The distance $D_{i,j}$ represents the Buffer distance between the UAVs, with the increasing of $D_{i,j}$, the collision possibility between the two UAVs is decreasing. Once the $D_{i,j} = 0$, which means the UAVs will collide.

Assuming that there are three UAVs in the cluster flying from its position to the target collaboratively, descripted in Fig.3. The UAV is flying by the path between its current and the target. In addition, the UAV moves to the $A(B, C)$ position at the time cost t (second), they are more likely to collide.

We project the three points in a two-dimensional plane as shown in Fig.4. In the 2-D plane, there are three points (A, B, C);, they represent the current position of each UAVs. Then calculate the distance D among all the points, and we assume that the $D_{A,B}$, $D_{C,B}$ are shorter than others, it means the UAV whose current position is B has to change its flight path. The new flight path will be re-planned according the new adding waypoint B' and its target B, the process will be descripted in part VI.

$$\overrightarrow{BB'} = a + b \tag{9}$$

$$C_{B'} = C_B + \overrightarrow{BB'} \tag{10}$$

Therefore, the way to find the waypoint B' is the key problem to the collision-resistant algorithm proposed in this

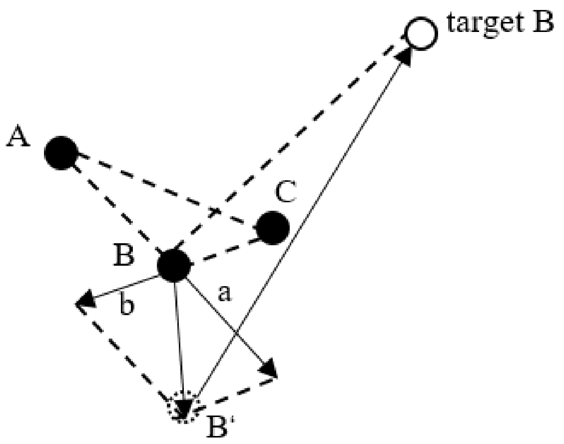

FIGURE 4. Points in the 2-D plane.

paper. The position vector $a = \overrightarrow{AB}$ and $b = \overrightarrow{CB}$ can be calculated by the C_A, C_B and C_C. the length a, b can be calculated by (9).

B. METHOD TO SCECURED COMMUNICATIONS

The UAVs connected with the ground base station through the wireless network, and communicate with others via the Ad-Hoc network. Data transmission between V2B (base station) and V2V is real-time.

In particular, the GPS coordinates and task information between drones require more timeliness protection. This provides protection for collision-resistant between the multi-UAV and flight path online planning. Therefore, accurate data transmission capable of resisting network attacks is crucial. A secure multi-UAV network needs to resist these attacks mainly including integrity attacks [34] and denial of service (DoS) attacks [35], [36]. A sub flight area can be demarcated by the coordinates of the waypoints in the assigned tasks of the UAV. The UAV are extremely vulnerable to GPS spoofing attacks, according to the drone GPS coordinates, if the current drone exceeds this area, it is considered suspicious showed as Fig.5, It will cut off the connection with other UAVs, and the others reconnect.

In multi-UAV applications, the main task is to monitor, sense, and disseminate the information collected. Since the data collected by multiple drones have the same characteristics, the data feature identifiers collected by each aircraft are compared, and the attacked UAV will be determined, and then take the next flight intensification.

V. TASK ALLOCATION METHOD

A. CLUSTERING ALGORITHM

In [35] and [40], the K-means algorithm is a very popular cluster method, it can divide data into clusters according to defined measurement standards, and the data in the same cluster have strong similarity with other group data that are called clustering. The similarity is calculated by finding the distance between the data object and the center of the cluster, and the distance from the center of the cluster is divided into

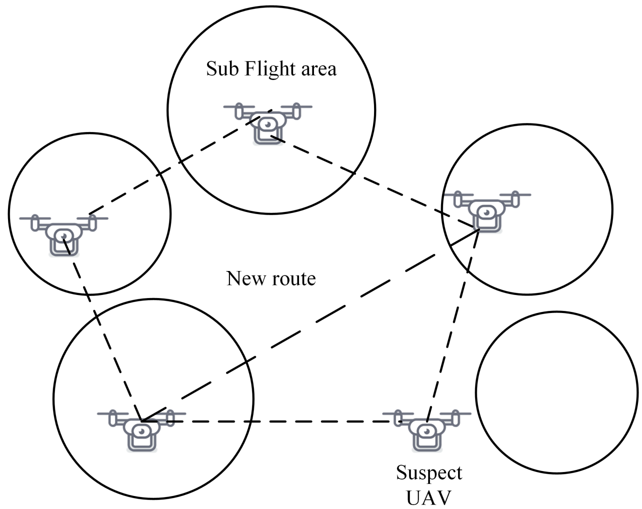

FIGURE 5. Connection between UAVs.

a cluster. The workflow of K-means are as follows: First, k objects are randomly selected, each object initially represents the average or center of a cluster. For each of the remaining objects, allocate them to the nearest cluster based on their distance from each cluster center. Then recalculate the average of each cluster, find the new cluster center, and then re-cluster. This process is repeated until the criterion function converges or reaches the maximum number of iterations The time complexity of the algorithm is O(nkt), where n is the number of all objects, k is the number of clusters, and t is the number of iterations. It cannot be applied to the multi-UAV task allocation directly, we change the measurement standards, this process will be descripted detailedly in the next section.

We use distance (5) between two waypoints i and j as the measurement standard. Firstly, we assume that the number of tasks is equal to the number of clusters, and then we select N_s objections randomly as the center of each cluster, we allocate the N_t waypoints to the nearest point of N_s centers by the distance (5) of t-th waypoint and the nearest center, and forming as N_s clusters. Then recalculate the average of each cluster, find the new cluster center, and then repeat clustering. This process is repeated until the criterion function converges or the maximum number of loops is reached. The workflow of waypoints clustering are shown as Fig.6.

From the Fig.7, the left image shows the 25 points in the coordinate system, which means 25 original waypoints without clustering by the proposed methods in the operating area. The right image shows that the 25 points are divided into 3 clusters and the 3 red dots represent the center of each group.

For each cluster, we add the take-off point N_0 to the top of the cluster, and then we find the best path by the Genetic-Algorithm (GA) path-planning method which is introduced by [38], the GA method is a typical evolution method, used widely in path planning, which has high efficiency, especially in the short path planning. Then the full task consists of

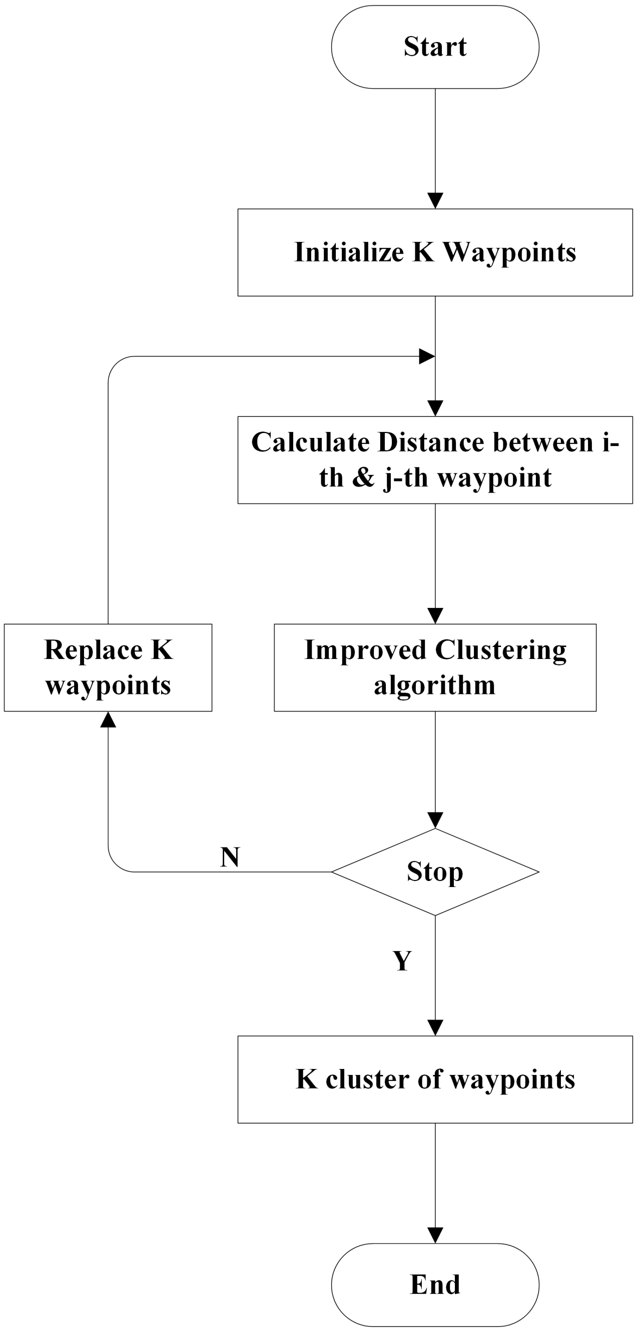

FIGURE 6. The process of clustering waypoints.

waypoints in sequence will be allocated to the UAVs according its energy storage metrics. Finally, multi UAVs fly by the sequence of waypoints.

B. OPTIMAL COUNT OF SUBTASK

Even though the previous methods can solve the task-allocation problem, in this section we will present a new method to enhance the effeteness. The K is equals to N_s, and the proposed task allocation method is based on the K-means algorithm, and the value of k. is most important. The k affect the quality of clustering, the result which is calculated

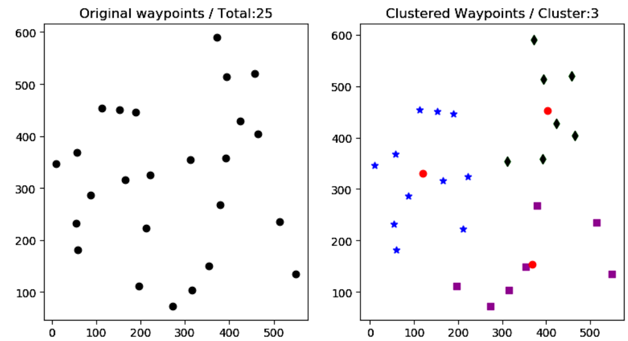

FIGURE 7. The image on the left shows the 25 original waypoint; the image on the right shows the 3 clusters.

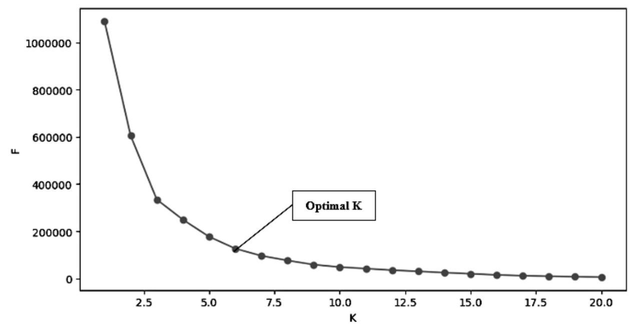

FIGURE 8. The relationship between F and K.

by k is not necessarily the best. Then we should find an optical k. We introduce that the coefficient F is Intra-cluster variance that represents the degree of aggregation of waypoint in the cluster, and calculated by the distance between center and each waypoint that is in the cluster. Given the waypoints, clustering by the proposed method in the last section, and we calculate the F. The relationship between F and K is showed as Fig.8.

VI. ONLINE PATH PLANNING ALGORITHM

In the process of multi-UAV collaborative execution, if a new target is added to the tasks, we must allocate the new target to a subtask, and find a new fly sequence of each subtasks. The key to this problem is to minimize the flight path length and improve real-time performance. Due to the urgency of the implementation of new target, most algorithms cannot guarantee the optimization of online task allocation.

The emergence of new waypoints is very random in the flight process. If they are found before, the task is executed, we have enough time to allocate the new waypoints to subtasks to find an optimal solution, and otherwise, we should find a method without optimization.

We mainly talk about the condition that a new waypoint is added in the flight process. Firstly, the waypoint should be allocated to a task. After the original task allocation in section V, we get 3 points clustering center, which have the mean and shorter distance to other waypoint in its cluster. Calculate the distance of new waypoint and each centers point

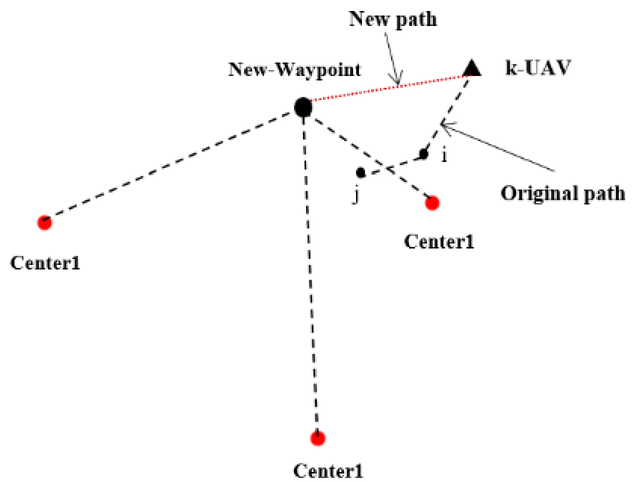

FIGURE 9. The simple new-waypoint allocation method.

showed as Fig.9. we allocate the new waypoint to the nearest center point, which gets an optimal flight length.

The new waypoint has been allocated to a subtask, then the UAV needs to re-plan the flight path, because the UAV has the original task in sequence. If the new waypoint is urgent and must be vested in T time which calculate from the added moment. We assume the UAV position where get the new task as the new start point, and calculate the flight length between all the left waypoints, then get the $t^k_{i,j}$ by (7). If $L^k_{i,j} > T$, then the UAV should fly to the new waypoint regardless of optimization, otherwise, the new waypoint can be visited after j-th waypoint is visited.

VII. SIMULTAION AND EXPERIMENTATION

A. COMPARISION

This section, we will verify the proposed multi-UAV task assignment algorithm through simulation experiments, and conduct two comparison experiments. The comparison test of N_v UAVs under one whole task, and comparing with other methods of multi-UAV task assignment algorithm. All the simulations are coded by PyCharm 2018.1.5(Community Edition) in the Windows 10 Enterprise Edition 64-Bits System, and the hardware environment of all the simulation is in a computer composed with Intel(R) Core(TM) i3-7100 CPU @3.90Ghz 3.91Ghz,8.00G Samsung DDR4 2400Mhz RAM.

Assuming that the whole task consists 60 waypoints and the point where UAVs take off, we allocate the whole task to N_v UAVs, where $\forall N_v \in (3.4.5.6)$. The runtime of algorithm concerns the timeliness of task allocation, the flight distance means the UAV energy cost. In order to avoid the randomness of the experiment, we run 20 times to find the average of the runtime and flight distance to ensure accuracy.

Assuming that the number of iterates is 6000, the $L^k_{\lim}$ is 2000(10m)which means the maximum flight distance of single UAV, the method without allocation iterates 6000 times, the number of the iterations by our algorithm is 6000/N_v. The experiment result shows in Table 1.

TABLE 1. The comparison between task allocated and the whole task.

N_k	Iterations	Distance(10m)	Average-Distance(10m)	Runtime(second)
1	6000×1	6462.89	6462.89	18.19
2	3000×2	3625.49	1812.75	12.90
3	2000×3	3529.30	1176.43	8.96
4	1500×4	3473.91	868.48	8.24
5	1200×5	3333.21	666.64	7.04
6	1000×6	3211.14	535.19	6.62

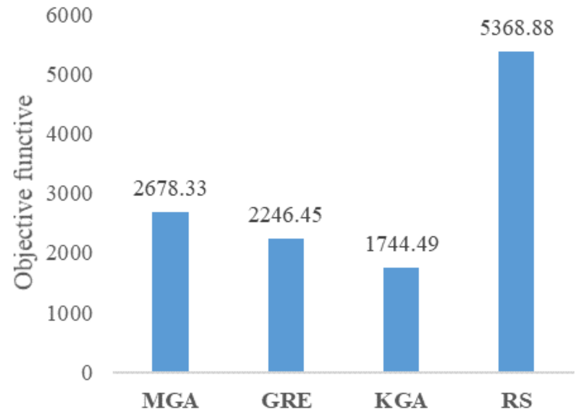

FIGURE 10. The comparison between serval methods.

We can see that with the increasing of N_v, the total flight distance of N_v UAVs is decreasing, which means the flight cost of multi-UAV is decreasing. The runtime of proposed algorithm is also decreasing, which means the task allocation process can be finished in a shorter time ensuring the timeliness. Obviously, viewing from where $N_v = 1$, distance $>L^k_{\lim}$, which means a single UAV cannot finish the whole task.

We conduct the experiment compared our method with other usual task allocation method such as the modified GA with multi-type genes (MGA) [39], the greedy algorithm, the random search (RS) method. Assume that there are 25 waypoints in the operation area, and we assign $N_v = 3$ UAVs fly to finish the whole task. The experiment readily 20 times for each method, the comparison results are shown in Fig.10. We can see that our method has the better performance compared with other methods, and the RS method has the worst performance. In the condition of our experiment environment, the average simulation time of these algorithm is 5.58 (MGA), 13.57(Gre), 6.15(KGA), 19.34(RS). Although the runtime of our algorithm is longer than MGA method, but it has the shorter flight length, which is the most critical factor in multi-UAV task allocation.

B. REAL EXPERIMENT

In order to verify the effectiveness of our proposed solution, we validated it using a real experimental platform. Our hardware experiment platform consists of three UAVs; the model of the UAV is DJI M100, equipped with an on-board Linux computer Manifold and other sensor device. All the UAV connect with each other by the Wireless communication device installed on its computer, showed in Fig.11,

FIGURE 11. The multi-UAV system.

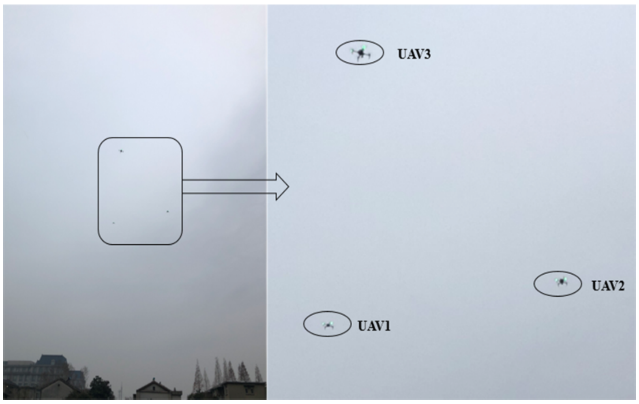

FIGURE 12. Three UAVs fly in the sky.

the UAV can exchange the data collected by the sensor in the real-time.

We conduct a real flight experiment on a 60 × 120 playground. From the figure 10, there are three UAVs landing at the nearby field. We set the velocity $V_k = 12(\mathrm{m/s})$, the acceleration $a_k = 6(\mathrm{m/s})$, and the commination lateness is 0.1s. Given the flight task consists of 25 waypoints, after allocating the whole task to three subtasks and distributing to the UAVs. Then the UAVs take off from the home point and fly by the sequence of waypoints. At one moment, three UAVs are flying in the sky and keep a relative position showed as Fig.12. and calculated the collision possibility.

We performed ten repeated experiments. The task allocation algorithm runs on the onboard computer for an average time of 9.38 s, and then the UAVs take off to perform the task. When multi-UAV are approaching, a UAV can re-plan its path to prevent the collision by calculating the collision possibility. In addition, in the actual flight process, the UAVs are affected by many factors; the GPS signal quality affected by the weather condition, the deviation of the real-time position of the drone, the flight speed and acceleration influenced by the wind in the sky, etc. Generally, the experimental results of actual flight are consistent with the simulation experiments, which proves the feasibility and accuracy of our algorithms.

VIII. CONCLUSION AND FUTURE WORK

For the multi-UAV task allocation problem, we formulated it as a combinatorial optimization problem, and then a mathematical model proposed. Our purpose is to find an optimal method to ensure that multi-UAV with many constraints can finish the whole task efficiently at lower cost. We propose the framework of multi-UAV task allocation, in addition, an optimal k which equals to the N_s is presented to optimize the task allocation algorithm further. We also propose the method of real-time path planning and task re-allocation to deal with the sudden problem such as new emergency targets. Finally, serval simulations verify the effectiveness of our presented algorithm.

Since the task allocation problem can be described as an m-TSP problem and NP-hard problem, meanwhile, the presented algorithm for multi-UAV task allocation is also an effective method, which can be extended to other similar issues. Next, in order to solve NP-hard problem effectively, we attempt to find a better method to satisfy the demand that the task allocation between more targets at lower cost.

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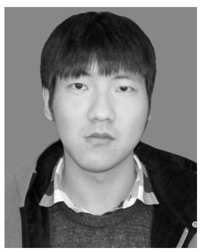

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