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• **RESEARCH PAPER** •

Joint Resource Allocation and Power Control for Radar Interference Mitigation in Multi-UAV Networks

Xinyi WANG[1,2], Zesong FEI[1,2*], Jingxuan HUANG[1], J. Andrew ZHANG[3] & Jinhong YUAN[4]

[1] *School of Information and Electronics, Beijing Institute of Technology, Beijing* 100081*, China;*
[2] *Beijing Institute of Technology Chongqing Innovation Center, Chongqing, China;*
[3] *School of Electrical and Data Engineering, University of Technology Sydney, NSW, Australia* 2007*;*
[4] *School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, NSW, Australia* 2052.

Abstract Navigation problems of unmanned air vehicles (UAVs) flying in a formation have been investigated recently, where collision avoidance is a significant issue to be addressed. In this paper, we study resource allocation and power control for radar sensing in a multi- unmanned aerial vehicle (multi-UAV) formation flight system where multiple UAVs simultaneously perform radar sensing. To cope with mutual radar interference among the UAVs, we formulate a joint channel allocation and UAV transmission power control problem to maximize the minimum signal-to-interference-plus-noise ratio (SINR) of the radar echo signals. We then propose a computationally practical method to solve this NP-hard problem by decomposing it into two sub-problems, i.e., channel allocation and transmission power control. An iterative channel allocation and power control algorithm (ICAPCA) is proposed to jointly solve these two sub-problems. We also propose a reduced-complexity greedy channel allocation algorithm (GCAA), which can also be used to provide an initial solution to ICAPCA. Simulation results show that the proposed ICAPCA and GCAA can improve the minimum SINR and radar sensing performance significantly.

Keywords multi-UAV network, radar sensing, channel allocation, power control

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1 Introduction

In the past few years, unmanned aerial vehicles (UAVs) have attracted increasing attention and are becoming an important component in mobile networks [1]. UAV communication is a promising paradigm for providing high-speed temporary connections at hotspots and under emergency situations [24]. Compared with conventional fixed infrastructure, UAVs can provide on-demand flexible deployment and larger service coverage. Besides, additional degrees of freedom can be exploited by designing the trajectory of UAVs [2]. Furthermore, UAV networks can also be integrated into cellular networks to provide higher throughput [3] and larger coverage [4].

Formation flying of multiple UAVs has been identified as the key technology for many cooperative missions [5]. There have been many works [5–8] on addressing the collision avoidance problems in a multi-UAV formation network. In [6], the authors proposed a dual-mode control strategy to determine the trajectory of cooperative UAV formation based on a modified Grossberg neural network. In [5], the

* Corresponding author (email: feizesong@bit.edu.cn)

formation control of multiple UAVs in an obstacle-laden environment was investigated, and both trajectory tracking and collision avoidance are both considered. In [7], the authors proposed a collision avoidance control algorithm for a multi-UAV system based on a bi-directional network connection structure. In [8], two types of UAV formulation communication methods were studied such that UAVs can continuously interact with the environment to obtain the optimal strategy.

In the aforementioned literatures, the collision avoidance of UAVs is mainly based on the communication among UAVs. However, in some complicated environment where predesigned trajectory and alerting via node-to-node communications cannot eliminate the possibility of collision, all UAVs in the formation have to sense the environment to avoid potential attack or collision [9]. To address this problem, radar based sensing technology is a promising method. In terms of collision avoidance for UAVs, some works have been done to determine the radar parameters of UAVs and control schemes for cooperative UAVs. In [10], a small-sized, light-weighted radar sensor was designed to realize obstacle awareness and avoidance for UAV. In [11], advantages and disadvantages of the radar systems for UAVs in S band, X band, as well as Ka band were investigated. In [12], based on chaotic UWB-MIMO waveform, a cognitive detect-and-avoid radar system was designed to help with autonomous UAV navigation. In [13], the authors investigated avoidance of path conflicts for UAV clusters through calculating the collision probabilities of UAVs under a given mission space and number of UAVs.

One fundamental issue for the radars on UAVs is the potential mutual interference due to multiple radars operating simultaneously on the same spectrum and direct line of sight, which may create ghost targets and degrade the target detection performance [14, 19, 22, 23]. There have also been some works addressing the interference mitigation issue in radar network [15–18, 20]. In [15], the weather radar networked system (WRNS) is studied. The authors proposed a novel frequency-shared WRNS, in which the waveform is modulated with an orthogonal code, and conducted matched filtering to mitigate inter-site interference. Besides, an interference-aware sidelobe suppressing algorithm is adopted to mitigate intra-site interference. In [16], a spectrum sensing multi-optimization (SS-MO) technique was investigated to help a radar to mitigate RF interference from others. In [17], a bioinspired filtering technique was proposed to reduce the computational complexity of SS-MO technique. In [18], the authors investigated the problem of adaptive power allocation in radar networks. Considering the transmit power constraint and minimum signal-to-interference-plus-noise ratio (SINR) requirement of each radar, a cooperative Nash bargaining power allocation game is formulated to improve the low probability of intercept performance. Note that in the aforementioned works, the mitigation of radar interference is realized via complicated signal processing techniques, which may increase the energy consumption of UAVs. One efficient technique to mitigate the mutual radar interference is to design the spectrum allocation scheme such that the radars that may introduce large interference to each other are allocated with different spectrum resources. In [20], the spectrum resources for automotive radars are allocated to mitigate the mutual interference among radars. Due to the geometrical constraint of the road model considered in [20], the mutual radar interference can be completely eliminated with four channels for four-lane road and two channels for two-lane road. Compared with automotive radars in vehicular networks, the line-of-direct case appears more often in UAV networks due to the wide open vision, i.e., the radar on one UAV may cause interference to the radar on any other UAV working in the same spectrum simultaneously.

In this paper, we study the radar interference mitigation methods for a multi-UAV formation flight system in a complicated environment, where all UAVs perform radar sensing to sense the non-cooperative targets and avoid collision. We investigate the joint optimization of the spectrum allocation and transmission power to mitigate the interference among radar sensors on different UAVs, which has not been reported in the literature. Due to the scarcity of the available frequency spectrum resource and the requirement for a large bandwidth in radar sensing in order to achieve a good distance resolution, part of UAVs will be assigned the same spectrum resource; thus, there will be mutual interference among the UAVs, whose power increases with the number of UAVs. Therefore, an efficient spectrum allocation algorithm is required to manage the mutual interference. In addition, the transmission power of each UAV should be adjusted appropriately. To this end, we propose a low-complexity branch-and-bound algorithm for spectrum allocation, and a geometric programming algorithm for power control. The two algorithms are then iteratively applied to jointly optimize the minimum SINR of radar echo signals among all UAVs in the network.

The main contributions of this paper can be summarized as follows.

(1) We consider a multi-UAV formation flight system (MUFFS) where multiple UAVs perform radar sensing to avoid potential attack or collision. A joint channel allocation and UAV transmission power optimization problem is then formulated to maximize the minimum SINR of radar echo signals among all UAVs in the MUFFS. We show that the problem is NP-hard.

(2) We propose a sub-optimal method to solve the formulated NP-hard problem, by decomposing it into two sub-problems: channel allocation and transmission power optimization. The two sub-problems are solved by branch-and-bound method and geometric programming, respectively. An efficient iterative channel allocation and power control algorithm (ICAPCA) is then proposed to solve the problem. In addition, to improve the efficiency of the proposed ICAPCA, we propose a greedy channel allocation algorithm (GCAA) to determine the initial channel allocation scheme.

(3) We compare the performance of the proposed algorithm with multiple schemes through simulation. Simulation results show that both the minimum SINR and detection probability of the proposed algorithms outperform that of traditional greedy method, and show that the performance of the proposed GCAA combined with power control can approach that of ICAPCA with a lower complexity, which indicates the effectiveness of the designed search order in GCAA.

The rest of this paper is organized as follows. In Section II, we present the system model of MUFFS. In Section III, we formulate a problem to maximize the minimum SINR of radar echo signals by jointly optimizing channel allocation and UAV transmission power. The proposed ICAPCA as well as GCAA are presented in Section IV, followed by convergence analysis. Simulation results are presented in Section V. In Section VI, we conclude the paper.

Notations: Unless otherwise specified, matrices are denoted by bold uppercase letters (i.e., $\mathbf{C}$), bold lowercase letters are used for vectors (i.e., $\mathbf{c}$), scalars are denoted by normal font (i.e., $c_{i,k}$), subscripts denote the rows of a matrix (i.e., $\boldsymbol{c}_i$ is the ith row of $\mathbf{C}$), $(\cdot)^T$ stands for transpose, $\|\cdot\|_0$ stands for zero norm.

2 System Model

In this section, we first describe the multi-UAV formation flight system (MUFFS), where multiple UAVs perform radar sensing simultaneously. Then we introduce the model of the echo signal and interference from other UAVs, based on which we formulate the expression of the SINR for each UAV.

2.1 System Description

We consider a MUFFS as shown in Fig. 1, which consists of one central station (CS), and a quasi-static multi-UAV formation consisting of N UAVs, denoted by $\mathcal{N} = \{1, 2, \cdots, N\}$. The UAVs fly in a formation and change their topology periodically. To avoid potential attack or collision, they separately transmit radar signals and perform radar sensing using the echo signals. We note that all UAVs work in a cooperative way, i.e., the locations of all UAVs are known to each other, and the UAVs in formation will not be viewed as an obstacle or non-cooperative target. In addition, the sensing information can be shared among all UAVs. To mitigate the mutual radar interference among UAVs, the CS conducts wireless resource allocation for UAVs. Herein, the resource allocation can also be performed by any UAV, since all UAVs work in a cooperative way, and the network topology is known to them all. However, to reduce the power consumption of UAVs, we deploy a central station to allocate resource for UAVs. In this paper, we mainly consider the aspects of spectrum resource allocation and transmission power control.

Remark 1. During resource allocation, we assume that the relative positions among all UAVs are fixed. The reasons are two-fold. On one hand, for the case of fast formation changing, e.g., the changing time is shorter than 1 second, note that the effective detecting range based on the proposed scheme in this paper is longer than 100m, the UAVs will not collide with the object outside the detecting range in such a short

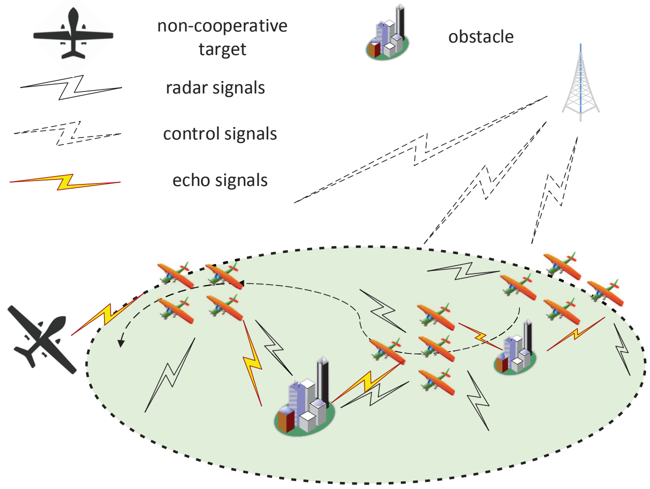

Figure 1 System model of MUFFS

time. Therefore, there is no need to keep sensing the environment in this period. On the other hand, for the case of slow formation changing, e.g., 100 milliseconds per slot, we can also divide the changing period into different time slots and perform resource allocation for each slot, since the positions of UAVs during the formation changing is also known to the CS. Also note that in 100 milliseconds, the moving distance of a UAV may be less than 1 meter, while hundreds of signal packets can be transmitted during this period; thus, the environment can be effectively sensed.

In terms of spectrum resource allocation, the transmission bandwidth of the network is divided into K channels of the same bandwidth, denoted by $\mathcal{K} = \{1, 2, \cdots, K\}$. Due to the scarcity of spectrum resource, we assume $N > K$. To specify the channel allocation for each UAV, we define an $N \times K$ binary integer matrix $\boldsymbol{C} = C_{n,k}$. When channel k is assigned to UAV n, we have $C_{n,k} = 1$, otherwise $C_{n,k} = 0$. For the sake of transmission quality as well as fairness among all UAVs, we assume each UAV is assigned one channel, that is, by denoting the i-th row of $\boldsymbol{C}$ as $\boldsymbol{c}_i$, we have $\|\boldsymbol{c}_i\|_0 = 1, i = 1, \cdots, N$. For the power control of each UAV, we define a vector $\boldsymbol{p}$ of length N, where the ith element represents the power of the ith UAV.

2.2 Signal and Interference Model

According to [25], the power of received echo signals from a target at a distance of R_i for the ith UAV can be characterized by radar range equation as

$$P_i = \frac{P_{t,i} G_{t,i}}{4\pi R_i^2} \times \frac{\alpha}{4\pi R_i^2} \times A_{e,i} \tag{1}$$

where the right-hand side includes three terms to model the physical process and propagation of signals. The first term in (1) represents the power density at a distance of R_i from the radar, where $P_{t,i}$ and $G_{t,i}$ are the transmission power and transmitter antenna gain of the ith UAV, respectively. The second term represents the power reflected by the target, where α is the radar cross-section area (RCS) of the target. The third term

$$A_{e,i} = \frac{G_{r,i} \lambda^2}{4\pi} \tag{2}$$

represents the effective aperture of the receiver antenna, where $G_{r,i}$ is the receiver antenna gain, and λ is the wavelength of the radio signal. In this paper, we assume the hardware for all UAVs are the same, and simplify $G_{t,i}$, $G_{r,i}$ and $A_{e,i}$ as G_t, G_r and A_e, respectively.

Assume that the ith UAV and the jth UAV are assigned the same spectrum resource. The interference power from the jth UAV to the ith UAV is only related to the first and last terms of the right-hand side in (1), and can be formulated as

$$P_{i,j} = \frac{P_{t,j} G_{t,j}}{4\pi d_{i,j}^2} \times A_{e,i}, \tag{3}$$

where $d_{i,j}$ is the distance between the ith UAV and jth UAV. As can be seen, the mutual radar interference power between two co-channel radars is inversely proportional to the square of the distance, while the power of the echo signal is inversely proportional to the quantic of the distance to the target. Therefore, the mutual interference is significantly stronger than the desired radar echo signals, and it is really harmful for radar sensing. Specifically, when a radar on a UAV is set to sense a target up to d meters away, another radar which is d^2 meters away and does similar sensing can introduce interfering signals with power comparable to the radar echo signal.

Further, the total interference for the ith UAV is expressed as

$$I_i = \sum_{j=1, j\neq i}^{N} \boldsymbol{c}_i \boldsymbol{c}_j^T P_{i,j}, \tag{4}$$

Note that the term $\boldsymbol{c}_i \boldsymbol{c}_j^T$ determines whether UAV i and UAV j are allocated with the same channel and whether there exists interference between UAV i and UAV j. Besides, the $\sum\limits_{j=1, j\neq i}^{N}$ operator is used to sum the total interference from all UAVs that have been allocated with the same channel as UAV i.

Therefore, the SINR of the echo signal for the ith UAV is given by

$$\gamma_i = \frac{P_i}{\sigma^2 + \beta I_i}, \tag{5}$$

where σ^2 is the variance of additive white Gaussian noise (AWGN) with zero mean, and β is the cross-correlation factor, reflecting the impact of the cross-correlation property of the radar signals for different UAVs, and is typically set as -20 to -30 dB [26].

3 Problem Formulation

In this section, we first formulate the problems of joint channel allocation and UAV transmission power control, and show that the optimization problem is NP-hard, and hence cannot be solved efficiently. We then propose a method via decomposing the problem into two sub-problems.

3.1 Problem Formulation

Since all UAVs have to detect the environment to avoid potential obstacles and attack separately, the minimum echo signal SINR for each UAV in this network is a key metric. We aim to maximize the minimum echo signal SINR of each UAV by optimizing the channel allocation and transmission power variables $\boldsymbol{C}$ and $\boldsymbol{p}$. The joint channel allocation and transmission power control problem can be formulated as follows:

$$\max_{\boldsymbol{C}, \boldsymbol{p}} \quad \min_{i} \quad \gamma_i \tag{6}$$

$$\text{s.t.} \quad P_{min} \leqslant P_{t,i} \leqslant P_{max}, \quad \forall i \in \mathcal{N} \tag{6a}$$

$$C_{i,k} \in \{0,1\}, \quad \forall i \in \mathcal{N}, \quad \forall k \in \mathcal{K} \tag{6b}$$

$$\sum_{k=1}^{K} C_{i,k} = 1, \quad \forall i \in \mathcal{N} \tag{6c}$$

Constraint (6a) limits the transmission power for UAVs. Note that the minimum power P_{min} is set as a positive number to guarantee that all UAVs are able to sense the environment. Constraint (6c) implies that each UAV can be assigned only one channel. Note that in calculating the SINR of echo signals, the distance from the ith UAV to a target, i.e., R_i, is implicitly required. Since the objective of radar sensing considered in this paper is to detect obstacles and avoid collision for flight formation, we assume that all UAVs are trying to detect the obstacles at a safe distance, such that there exists sufficient time for UAVs to react to the detected obstacles. This safe distance is adopted as the target distance in this paper. Although the safe distances for different UAVs may differ due to different security levels, in this paper, without loss of generality, we assume they are approximately the same. In the following theorem, we show that the optimization problem (6) is NP-hard.

Theorem 1. Problem (6) is NP-hard.

Proof. We consider the case that we do not perform transmission power control, then problem (6) can be simplified as a channel allocation problem. The channel allocation problem can be seen as an extension of graph partition problem with the purpose of minimizing the mutual interference in each sub-graph. Since graph partition problem has been proved to be NP-complete in [27], the channel allocation problem is also NP-hard, i.e., we cannot solve the channel allocation problem in polynomial time. Thus, the problem (6) is NP-hard, and it cannot be solved in polynomial time.

3.2 Problem Decomposition

To solve the problem (6) efficiently, we decompose it into two sub-problems, i.e., channel allocation sub-problem and transmission power control sub-problem. In the channel allocation sub-problem, the transmission power of each UAV is considered to be fixed. The channel allocation sub-problem is written as

$$\max_{\boldsymbol{C}} \quad \min_{i} \quad \gamma_i \tag{7}$$
$$\text{s.t.} \quad C_{i,k} \in \{0,1\}, \quad \forall i \in \mathcal{N}, \quad \forall k \in \mathcal{K} \tag{7a}$$
$$\sum_{k=1}^{K} C_{i,k} = 1, \quad \forall i \in \mathcal{N} \tag{7b}$$

With the channel allocation matrix $\boldsymbol{C}$ being fixed, the transmission power control sub-problem can be expressed as

$$\max_{\boldsymbol{p}} \quad \min_{i} \quad \gamma_i \tag{8}$$
$$\text{s.t.} \quad P_{min} \leqslant P_{t,i} \leqslant P_{max}, \quad \forall i \in \mathcal{N} \tag{8a}$$

4 Joint channel allocation and UAV transmission power Control

In this section, we propose an efficient iterative algorithm, i.e., ICAPCA, to solve the problem (6) by iteratively solving the sub-problems (7) and (8). Specifically, to solve the channel allocation sub-problem (7), we propose a low-complexity branch-and-bound algorithm. For the power control sub-problem (8), optimization for the whole network is decomposed into optimization for each sub-network where the UAVs are assigned the same channel, and is then formulated through geometric programming. In the following subsections, we first introduce algorithms for solving the two sub-problems, we then present the ICAPCA and its convergence and complexity analysis.

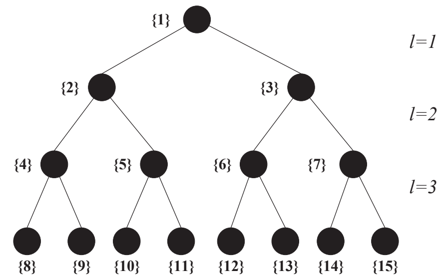

Figure 2 Illustration of the search space tree with $K = 2$ and $N = 3$

4.1 Channel allocation Algorithm

In this subsection, we focus on solving the channel allocation sub-problem (7). Substituting (1), (3) and (4) into (7), we have the objective function as follows:

$$\max_{\boldsymbol{C}} \quad \min_{i} \quad \frac{P_{t,i}E_i}{\sigma^2 + \sum\limits_{j=1,j\neq i}^{N} \boldsymbol{c}_i\boldsymbol{c}_j^T P_{t,j}F_{i,j}}, \tag{9}$$

where $E_i = \frac{G_{t,i}A_{e,i}\sigma}{(4\pi)^2 R_i^4}$ and $F_{i,j} = \frac{G_{t,j}A_{e,i}}{4\pi d_{i,j}^2}$ are fixed. It can be readily seen that the sub-problem (7) is also a NP-hard problem. The difference between the original problem (6) and the sub-problem (7) is that problem (6) is a mixed integer programming problem and can be hardly solved efficiently, while sub-problem (7) is a binary integer programming problem. A direct idea for solving this kind of NP-hard problems is to relax the binary variable into continuous variables. However, due to the mutual interference among different UAVs, the continuity relaxed problem is still non-convex with respect to $\boldsymbol{C}$.

Indeed, since each UAV can only be assigned one channel, the search space of the channel allocation matrix $\boldsymbol{C}$ can be considered as a K-ary tree, denoted as *search space tree*. The lth layer of the K-ary tree denotes the allocation for the lth UAV, assuming the allocation for UAVs whose indices are smaller than l has been determined. The kth fork branched from one node in the lth layer represents that the kth channel is assigned to the lth UAV. An example of the search space tree with $K = 2$ and $N = 3$ is illustrated in Fig. 2. At the root node, all the variables in $\boldsymbol{C}$ are not determined, while each leaf node represents a channel allocation scheme for all UAVs. For the 6th node, it represents that the first two UAVs are assigned channel #2 and #1, respectively, while the third UAV has not been assigned. For the 10th node, the three UAVs are assigned channel #1, #2, #1, respectively.

To obtain an optimal solution through the tree searching, branch-and-bound method is a promising candidate, which has been used in [21] to solve the binary integer programming problem. In a conventional branch-and-bound method, through the branch operation, the problem is divided into multiple sub-problems, each corresponding to one subspace of the whole search space. In each subspace, a bound value is calculated to determine whether continuing to branch or discarding this subspace. In this way, the time complexity of conventional branch-and-bound method may be extremely high, and in the worst case it is the same as that of exhaustive searching scheme, i.e., $O(K^N)$. Since the proposed MUFFS may work in an emergency scenario, the algorithm complexity and implementation time are critical. Therefore, we propose a novel low-complexity branch-and-bound method to determine the channel allocation.

In what follows, we first introduce the proposed GCAA to generate a feasible initial solution, which serves as the lower bound of the final solution and helps with the pruning of the search space.

To facilitate the understanding of the GCAA, we first introduce the important concepts of intensity metric and UAV set.

Definition 1. To measure the potential interference between two UAVs, the **intensity metric** between the ith UAV and the jth UAV is defined as

$$M_{i,j} = \frac{G_t}{4\pi d_{i,j}^2} \times A_e, \tag{10}$$

Definition 2. The set of UAVs that are assigned the same channel is a **UAV set**. The UAV set corresponding to the kth channel is defined as the kth UAV set, denoted by $\mathcal{N}_k$.

As can be seen, the only difference between (10) and (3) is the transmission power. This is because the transmission power in this paper is adjustable, and we intend to utilize the intensity metric to model the equivalent channel gain of the interference among different UAVs. In other words, the intensity metric reflects the interference when transmission powers of UAVs are all the same.

1) Greedy channel allocation Algorithm: The GCAA is essentially a path search procedure on the search space tree. At the lth layer, the lth UAV is assigned one channel so that the interference introduced by the UAVs that have been already assigned this channel to the lth UAV should be minimum among all channels.

Although the principle of GCAA is simple, it should be noted that the search order has a significant impact on the performance. Therefore, in what follows, we will introduce a low-complexity method to determine the search order. This method includes two parts, i.e., determining the first K UAVs and then the remaining UAVs.

For determining the first K UAVs, the optimal solution is to find K UAVs among which the total distance is the smallest. However, the complexity of searching such UAV set is C_N^K, which may be too large for large N and K. Therefore, we select the first K UAVs in a greedy manner. Specifically, we first select two UAVs among which the distance is the shortest. Then we select the UAV that is closest to the already selected UAVs one by one. With the indices of the first K UAVs determined, we assign the K orthogonal channels to them.

For determining the search order of the remaining UAVs and their corresponding channels, we propose to determine the index of the next UAV to be allocated in the following manner:

$$\widetilde{i} = \arg\max_i \quad \frac{1}{(K-1)} \left(\sum_{k=1}^{K} \sum_{j \in \mathcal{N}_k^C} M_{i,j} - \min_k \sum_{j \in \mathcal{N}_k^C} M_{i,j} \right), \tag{11}$$

where $\mathcal{N}_k^C$ represents the set of indices of UAVs that have been allocated with the kth channel. The term $\sum\limits_{k=1}^{K} \sum_{j \in \mathcal{N}_k^C} M_{i,j}$ represents the total interference introduced by the ith UAV to the UAV sets when the ith UAV is allocated with the corresponding channel. The term $\min\limits_k \sum_{j \in \mathcal{N}_k^C} M_{i,j}$ represents the interference introduced by the ith UAV to the UAV set that corresponds to the minimum intensity metric. We intend find the UAV which would introduce largest average interference when not allocated the channel with minimum intensity metric. The index of the channel allocated to the selected UAV can be expressed as

$$\widetilde{k} = \min_k \quad \sum_{j \in \mathcal{N}_k^C} M_{\widetilde{i},j}. \tag{12}$$

The detailed process of GCAA is presented in Algorithm 1. In line 1 to 4, the indices of the first K UAVs are determined. In line 5 to 10, we successively select UAVs and allocate the channels to them. In each iteration, the complexity is $O(K)$. Therefore, the total complexity of GCAA is $O(KN)$. One example of the channel allocation result based on GCAA is shown in Fig. 3, where $K = 4$ and $N = 20$. As can be seen from the figure, for each set consisting of K closest UAVs, it is very likely that they are assigned different channels.

2) Low-complexity Branch-and-Bound method: The proposed low-complexity branch-and-bound method can be regarded as a breadth-first searching on the search space tree level by level. The branch and bound operations are performed at each level. Specifically, at each level, the bound of each node is calculated and compared with the global upper bound. At most M nodes whose bounds are larger than the current upper bound are preserved to branch. The initial global upper bound is set as the solution given by GCAA.

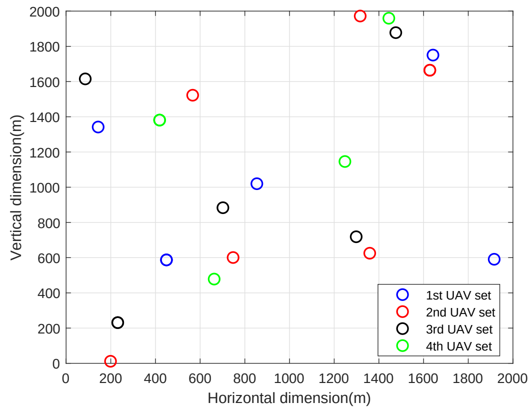

Figure 3 An example of the channel allocation result using GCAA

Algorithm 1 Greedy channel allocation Algorithm

1: Select two UAVs among which the distance is the shortest.
2: **for** $i = 3, \cdots, K$ **do**
3: Select the UAV which is closest to the already selected UAVs.
4: **end for**
5: Assign K orthogonal channels to the K selected UAVs.
6: **for** $i = K+1, \cdots, N$ **do**
7: Determine the index of next UAV to be allocated according to (11)
8: Determine the channel assigned to the $\widetilde{i}$th UAV according to (12)
9: Add the index $\widetilde{i}$ to the $\widetilde{k}$th UAV set, $\mathcal{N}_k$.
10: **end for**

For the bound calculation of each node, only the interference of UAVs that are already assigned channels is considered. To decrease the complexity in calculating the upper bound of the objective function (9) for each node, e divide all UAVs into different UAV sets in terms of the channels allocated, and express the upper bound of (9) as follows.

$$\widetilde{B}_u = \min_k \min_{i \in \mathcal{N}_k^C} \frac{P_{t,i} E_i}{\sigma^2 + \sum\limits_{j \in \mathcal{N}_k^C, j \neq i}^{N} P_{t,j} F_{i,j}}. \tag{13}$$

The bounds of all nodes at each level are then sorted and compared with the global upper bound. The nodes whose upper bound is lower than the global upper bound are then fathomed. In addition, to reduce the complexity, a maximum searching width M is defined, i.e., at most M nodes are preserved at each level. The preserved nodes are then branched continually until the last level.

It should be noted that the search order has also an impact on the performance as well as complexity of the branch-and-bound method, since with an advantageous search order, more nodes can be fathomed, and the searching process would become more efficient. To that end, we utilize the search order in GCAA so that we can improve the efficiency of the branch-and-bound method as well as avoid the further complexity of designing another search order. Details of the low-complexity branch-and-bound method are shown in Algorithm 2. At each level, at most M nodes are preserved according to the corresponding bound, and each of them is then branched to K nodes at the next level. The complexity of the proposed low-complexity branch-and-bound method is $O(KMN)$, which is much smaller than $O(K^N)$.

We also note that both proposed spectrum allocation schemes are also applicable to the multi-cell systems [29, 30]. On one hand, the spectrum allocation criterion is to allocate different bands to adjacent cells such that the inter-cell interference can be mitigated, which is consistent with the design criterion of the proposed GCAA scheme. In addition, the proposed low-complexity branch-and-bound scheme

Algorithm 2 Low-complexity branch-and-bound method

Input: $B_u \leftarrow$ the initial upper bound given by GCAA;
$M \leftarrow$ the maximum list size;
1: **for** $i = 1, \cdots, N-1$ **do**
2: Calculate the upper bound of each node at the ith level based on (13).
3: Sort the upper bound of each node and fathom the nodes whose upper bound is lower than B_u.
4: Preserve up to M nodes with the largest upper bounds.
5: Branch the preserved nodes to the next level.
6: **end for**
7: Calculate the minimum SINR for each node at the Nth level and select the node with the largest minimum SINR.
8: Allocate the channels to the UAVs in the manner corresponding to the selected node.
Output: the channel allocation result

can amend the allocation result obtained by the GCAA scheme. Therefore, both proposed spectrum allocation schemes can be applied to multi-cell systems.

4.2 Power Control Algorithm

In this subsection, we study how to solve the transmission power control sub-problem (8). Note that through dividing all UAVs into different UAV sets that are assigned orthogonal channels, the mutual interference between two UAVs belonging to different UAV sets can be eliminated. Therefore, the sub-problem (8) can be further divided into K sub-problems, each for one UAV set. The kth sub-problem can be expressed as follows

$$\max_{\boldsymbol{p}_{\mathcal{N}_k}} \quad \min_{i\in\mathcal{N}_k} \quad \frac{P_{t,i}E_i}{\sigma^2 + \sum\limits_{j\in\mathcal{N}_k, j\neq i}^{N} P_{t,j}F_{i,j}}, \tag{14}$$

$$\text{s.t.} \quad P_{min} \leqslant P_{t,i} \leqslant P_{max}, \quad \forall i \in \mathcal{N}_k \tag{14a}$$

where $\boldsymbol{p}_{\mathcal{N}_k}$ represents the transmitting power of the UAVs using the kth channel. The above problem is non-convex, but can be easily cast as a geometric programming problem by taking the inverse of the SINR as follows [31]:

$$\max_{\boldsymbol{p}_{\mathcal{N}_k}, t} \quad t \tag{15}$$

$$\text{s.t.} \quad P_{min} \leqslant P_{t,i} \leqslant P_{max}, \quad \forall i \in \mathcal{N}_k \tag{15a}$$

$$\frac{\sigma^2 + \sum\limits_{j\in\mathcal{N}_k, j\neq i}^{N} P_{t,j}F_{i,j}}{P_{t,i}E_i} \leqslant \frac{1}{t} \tag{15b}$$

This allows us to solve the transmission power control sub-problem via geometric programming [32].

4.3 Iterative Channel Allocation and Power Control Algorithm

In this subsection, we introduce the ICAPCA to solve problem (6), where channel allocation and transmission power control are iteratively solved. Specifically, we first obtain the initial channel allocation solution via GCAA, denoted by $\boldsymbol{C}^{(0)}$, based on which the initial power control solution is obtained, denoted by $\boldsymbol{p}^{(0)}$. We then perform iterations of low-complexity branch-and-bound based channel allocation and geometric programming based power control until the objective function converges or the maximum iteration number is reached.

In what follows, we prove the convergency of the ICAPCA.

Theorem 2. The proposed ICAPCA is convergent.

Table 1 Simulation Parameters

Center frequency	35 GHz [10]
Antenna gain	38 dB [10]
Radar cross-section	30dBsm [28]
Maximum UAV transmission power	47 dBm
Minimum UAV transmission power	30 dBm
Cross-correlation factor β	-20 dB [26]
Algorithm convergence threshold ϵ	0.01
Maximum iteration number	5
Maximum searching width M	8
Default distance of non-cooperative targets to be sensed	100 m
Default number of channels	4
Bandwidth of each channel	200 MHz
SINR threshold for successful detection T	10 dB [28]

Proof. First, we consider channel allocation in the $(n+1)$-th iteration. Note that the allocation solution and its corresponding minimum SINR will not be updated unless the minimum SINR obtained through the low-complexity branch-and-bound method is larger than the current minimum SINR. Therefore, we have

$$\gamma_{min}(\boldsymbol{C}^{(n+1)}, \boldsymbol{p}^{(n)}) \geqslant \gamma_{min}(\boldsymbol{C}^{(n)}, \boldsymbol{p}^{(n)}), \tag{16}$$

where $\gamma_{min}(\cdot)$ denotes the minimum SINR with the corresponding parameters.

When solving the power control sub-problem, the optimal power control $\boldsymbol{p}^{(n+1)}$ with $\boldsymbol{C}^{(n+1)}$ is obtained via geometric programming. Thus we have

$$\gamma_{min}(\boldsymbol{C}^{(n+1)}, \boldsymbol{p}^{(n+1)}) \geqslant \gamma_{min}(\boldsymbol{C}^{(n+1)}, \boldsymbol{p}^{(n)}), \tag{17}$$

Therefore, in the $(n+1)$th iteration, we have

$$\begin{aligned} \gamma_{min}(\boldsymbol{C}^{(n+1)}, \boldsymbol{p}^{(n+1)}) &\geqslant \gamma_{min}(\boldsymbol{C}^{(n+1)}, \boldsymbol{p}^{(n)}) \\ &\geqslant \gamma_{min}(\boldsymbol{C}^{(n)}, \boldsymbol{p}^{(n)}), \end{aligned} \tag{18}$$

i.e., the objective function is non-decreasing. Also note that the minimum SINR of a network cannot increase unlimitedly, i.e., there is an upper bound for the objective function. Therefore, the proposed ICAPCA is convergent.

5 Simulation Results

In this section, we evaluate the performance of the proposed GCAA and ICAPCA. The location of the UAVs are randomly and uniformly distributed in a 2-dimension area of 2 km × 2 km. The simulation parameters are listed in Table 1. The proposed algorithms are compared with three other schemes: (1) random channel allocation with maximum transmission power, denoted as “random+max power”; (2) random channel allocation with power control (PC), denoted as “random+PC”; (3) a greedy channel allocation [20] with power control, denoted as “greedy [20]+PC”.

Before the performance comparison, we show the convergence behaviour of the proposed ICAPCA in Fig. 4. It can be observed that the max-min SINR achieved by the proposed ICAPCA increases quickly and converges in 3 iterations. Specifically, The obtained minimum SINR at iteration 0 corresponds to the “random+max power” scheme, while the minimum SINR at iteration 1 corresponds the proposed GCAA scheme followed by power control. The minimum SINR of the proposed ICAPCA scheme converges at the 3rd iteration; thus, the value at iteration 3 corresponds to the ICAPCA scheme.

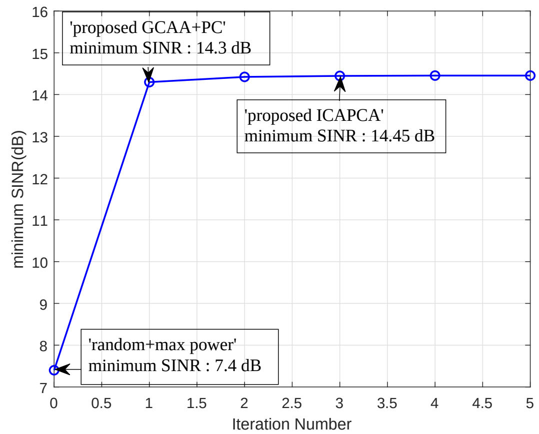

Figure 4 Minimum SINR v.s. iteration number ($K = 4$, $N = 20$).

Table 2 Performance comparison between Monte Carlo simulation and proposed ICAPCA

Optimal minimum SINR via Monte Carlo simulation	Minimum SINR via proposed ICAPCA	Proportion of the Monte Carlo results better than proposed ICAPCA
14.6591 dB	14.5265 dB	0.5 %

It should also be noted that due to the non-convexity of the original problem, an iterative algorithm may converge to a poor local solution point, depending on the adopted initial channel allocation scheme. Fortunately, with the help of the searching order and the usage of the geometric topology of the multi-UAV network, the performance of the proposed ICAPCA will hardly converge to a poor result. To justify this, we randomly select initial channel allocation schemes 1000 times for ICAPCA to approach the optimal solution. The performance gap between the best value among the obtained results and the proposed ICAPCA as well as the proportion of the results which is better than that of the proposed ICAPCA are shown in Table 2. As can be seen, the performance gap between the proposed ICAPCA and the best value obtained via Monte Carlo simulation is less than 0.15 dB, and the proportion of the results that are better than those of the proposed ICAPCA is only 0.5%, which implies the effectiveness of the proposed GCAA in producing the initial channel allocation scheme for ICAPCA.

Fig. 5 depicts the minimum SINR at various SNRs. The SNR is defined as the ratio between the maximum transmission power and the noise power. The cross-correlation factor β is used through (5) due to the matched filtering operation. Here the SNR is for the signal after the matched filter. As can

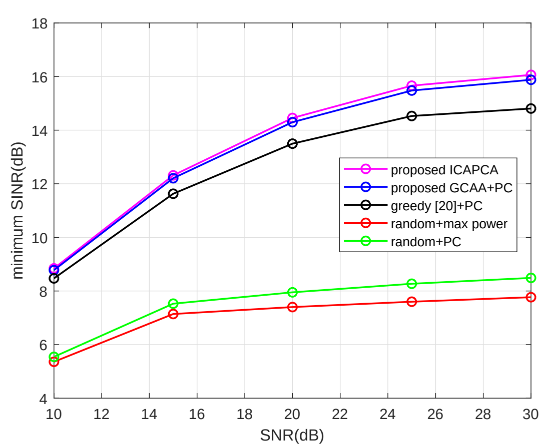

Figure 5 Minimum SINR v.s. SNR ($K = 4$, $N = 20$).

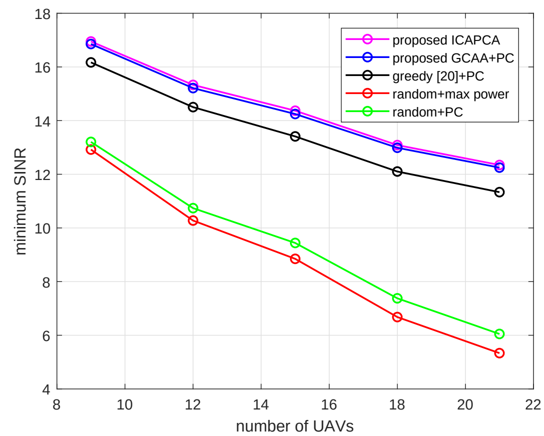

Figure 6 Minimum SINR v.s. number of UAVs ($K = 3$, SNR = 20 dB).

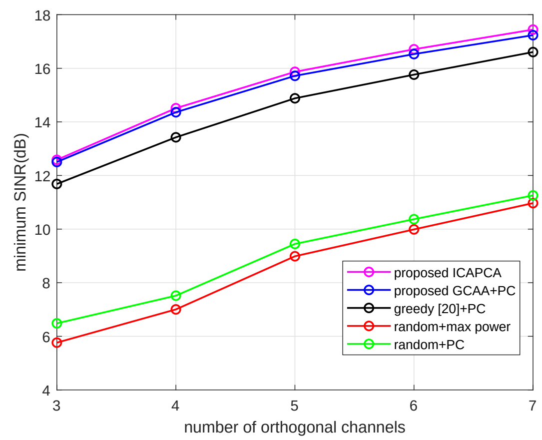

Figure 7 Minimum SINR v.s. number of channels ($N = 20$, SNR = 20 dB).

be seen, the proposed algorithms outperforms the random schemes as well as the greedy scheme in [20], and the performance gap increases with the SNR increasing. This is because for a lower SNR, the noise power and interference power are of equal importance, while for a higher SNR, the interference power has a more significant impact on the SINR; thus, designing the allocation scheme can lead to a larger gain. In addition, it is shown that the performance of GCAA and ICAPCA is close, which indicates the effectiveness of the designed search order in GCAA.

Fig. 6 shows the minimum SINR with various numbers of UAVs, where the number of channels is set as $K = 3$. It is shown that the minimum SINR decreases with the number of UAVs. This is not only because of the increasing number of UAVs in each UAV set, but also due to the shorter distance among the UAVs. In addition, the performance gap between the proposed and other schemes increases with the number of UAVs, which indicates that an efficient channel allocation scheme is needed when dealing with a large multi-UAV network.

In Fig. 7, the minimum SINR with various numbers of channels is illustrated, where the number of UAVs is set as $N = 20$. As can be seen, the minimum SINR increases with the number of channels, since there would be less UAVs in each UAV set for a larger number of channels.

In Fig. 8, we show the successful detection probability versus the target distance, where the numbers of channels and UAVs are set as $K = 4$ and $N = 20$, respectively, and the SNR is set as 20 dB. We assume that a successful detection could be achieved if the SINR is larger than a certain threshold T. It is shown that using the proposed GCAA and ICAPCA, we can successfully detect a target at a much longer distance compared with the random allocation scheme. Meanwhile, the performance gap between

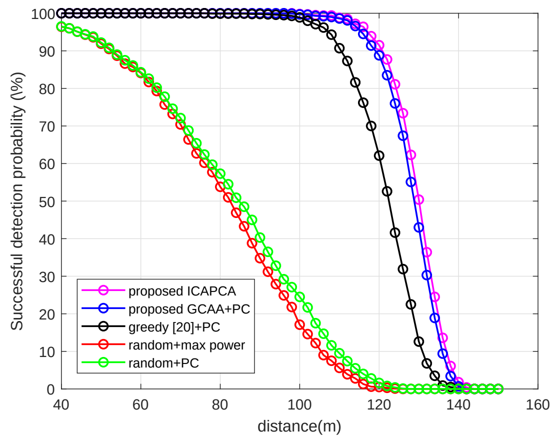

Figure 8 Successful detection probability v.s. target distance ($K = 4$, $N = 20$, SNR = 20dB).

the proposed schemes and the greedy scheme in [20] is also significant.

6 Conclusion

In this paper, we studied joint resource allocation and power control for radar sensing in a multi-UAV formation flight system where multiple UAVs simultaneously perform radar sensing. To mitigate the mutual radar interference among UAVs and maximize the minimum SINR for the UAVs in the network, we proposed the ICAPCA for nearly optimal channel allocation and power control. We also proposed the GCAA to provide an initial solution for the ICAPCA, speeding up the convergence and reducing the complexity. Simulation results showed that both GCAA and ICAPCA achieve excellent performance and can detect targets effectively at a long distance.

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