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Special Focus on Wireless Communications with Unmanned Aerial Vehicles (UAVs)

Leveraging partially overlapping channels for intra- and inter-coalition communication in cooperative UAV swarms

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Abstract Cooperative UAV swarms typically adopt coalition-based network structures for executing tasks more efficiently. Coalition heads in such networks need to do both intra- and inter-coalition communication and may operate on different channels. While being equipped with multiple transceivers or switching among channels are alternative methods, this option would result in larger payload or incur delays. Fortunately, partially overlapping channels (POCs) can be used to forward messages on different channels since communication can be made on adjacent overlapped channels. This can help realize both intra- and inter-coalition communication with heads being equipped with only one transceiver and no switching. Therefore, this paper proposes a POC-based communication method where each coalition selects one of the POCs and UAVs in the same coalition operate on the same channel. While POCs enable information exchange among coalitions, they also incur inter-coalition interference and therefore the POC access problem is investigated. Owing to the coupled relationships among the strategies of coalitions, the problem is a combinatorial optimization one and an online learning algorithm is proposed. The algorithm is distributed and reduces the computation complexity to a great extent. Based on the knowledge of the potential game theory, the algorithm is proved to converge to the optimal solution of each stage asymptotically. Under three representative settings, simulations are made to verify the effectiveness of the proposed method.

Keywords UAV swarm, coalition, partially overlapping channel, learning algorithm, game theory

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1 Introduction

Cooperative search is one of the main applications of UAV swarms [1–5]. Working in a unit of coalition (also called cluster or team) can finish tasks efficiently [6, 7] and communication among UAVs is essential during the execution [8, 9]. In such networks, both intra- and inter-coalition communications require spectrum resources and the spectrum access for each coalition should be well designed to realize both interference avoidance and information exchange. However, existing researches about UAV swarms mainly focused on path planning [10], information merging [11] or coalition formation [12–15], while paid little attention on communication. Therefore, it is necessary and meaningful to investigate the spectrum access problem in coalition-based UAV swarms.

Technically, there are several challenges in this problem. First, adjacent coalitions tend to work on orthogonal channels to avoid inter-coalition interference, while adjacent coalition heads should work on the same channel to perform information exchange. This can be realized by switching or being equipped with multiple transceivers. However, switching incurs delays, or even failures, and consumes non-negligible amount of energy [16–18], while being equipped with multiple transceivers is a burden to UAVs since they are payload-constraint [19–22]. While some devices, such as multi-protocol transceivers,

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can incorporate multiple channels, the cost of hardware is higher. Therefore, how to find a stable and low-cost communication method is challenging. Second, while conducting the search task requires multiple coalitions and multiple stages, the resources, e.g., spectrum and storage, are limited. This makes the impact of the spectrum access strategy of each coalition in each stage be coupled and therefore the problem is a complex combinatorial optimization one. How to find the optimal solution of the problem is challenging. Third, as the network scales up, traditional centralized methods [23, 24] may be inefficient or even unapplicable since the computation complexity increases [25, 26]. How to find an efficient method to solve this problem is challenging.

Fortunately, partially overlapping channels (POCs) have been demonstrated to be suitable for forwarding transmissions on different channels, and some signal processing methods and medium access control (MAC) mechanisms have been proposed to make this feasible [27–29]. Compared with orthogonal channels, where adjacent channels have enough far frequency separation, adjacent POCs are not separated far so that signals from overlapping channels can be heard. This relaxes the requirement for multiple transceivers and switching. Therefore, a POC-based communication method is established and leveraged in this paper where adjacent coalitions work on overlapping channels and UAVs can do both intra- and inter-coalition communication with only one transceiver and without switching. In addition, to address the high computation complexity, we resort to the machine learning methods [30–33] in which users update repeatedly and individually. A spatial adaptive play (SAP)-based online distributed learning algorithm is proposed. The algorithm is executed by each individual coalition head, and the computation complexity is reduced to a great extent. By resorting to the potential game theory, we prove that the proposed algorithm can achieve the optimum asymptotically in each stage. Simulations are made to validate the effectiveness of the proposed method.

The contributions of this paper are as follows.

- A POC-based communication method is proposed to realize both intra- and inter-coalition communication in cooperative UAV swarms. The method aims at avoiding inter-coalition interference and realizing information exchange among coalitions at the same time while requiring only one transceiver and no channel switching.
- A SAP-based online learning algorithm is proposed. The algorithm is distributed and with low-complexity. Based on the knowledge of the potential game theory, the algorithm is proved to be able to converge to the optimal solution in each stage asymptotically.
- Simulation results verify the effectiveness of the proposed method. Three representative trajectories are given to compare the results under different settings. Compared with the method which requires two transceivers or channel switching, the proposed method achieves higher efficiency under many conditions.

The rest of the paper is organized as follows. Related work is given in Section 2. The system model and the problem formulation are given in Section 3. The learning algorithm is proposed and analyzed in Section 4. Simulation results are given and analyzed in Section 5. Section 6 concludes the paper.

2 Related work

Many researchers realized that UAV swarms working in a unit of coalition perform better compared to working individually. Some work has been made under the coalition-based structure. Specifically, authors of [12–15] investigated how to form coalitions in cooperative missions. They designed different coalition formation algorithms to fulfill the target resource requirements. Authors of [6] proposed an algorithm to track moving targets using a UAV cluster. Authors of [10] investigated the path planning problem and proposed an information-theoretic co-evolutionary algorithm. These researches paid little attention on communication among UAVs, only taking the communication range as a constraint.

Some researchers made contributions to UAV communication networks [34–37]. However, they mainly focused on relay [34, 35], trajectory [36] or deployment [37] optimizations, but did not mention the spectrum access problem and networks were not under the coalition-based structure. Authors of [9, 26] did relevant work. Specifically, in [9], the joint channel and time slot optimization problem was investigated to satisfy heterogeneous requirements where UAVs could select several channels or slots to communicate. This required UAVs to be equipped with more than one transceiver. In [26], the intra-coalition communication was focused on and the spectrum access problem was investigated to alleviate inter-coalition interference. UAVs may need to switch to different channels if they wanted to communicate with those in other coalitions. It can be seen that, the above studies did not consider both the internal and external communication in coalition-based UAV swarms, which is very important in cooperative search. Moreover, the switching cost and the payload constraint were not considered which should not be ignored for UAVs.

Traditional orthogonal channels have enough frequency separations so that signals from different channels will not be heard. By comparison, the central frequencies of adjacent POCs are not separated far so that signals from overlapping channels can be heard. Many researchers treated the signal from adjacent channels as a harm and made several investigations on the POC access problem to alleviate such interference [38–46]. However, the benefit that POCs can be used to forward transmissions on adjacent channels and thus relax the requirement of multiple transceivers and switching was less exploited. This idea was first mentioned in [27], in which a simple example of a multi-hop scenario was given to show the feasibility of such transmission. After that, authors of [28, 29] exploited the overlapping character of adjacent channels and put forward a counter-intuitive approach for efficient broadcast in multi-channel networks. While the signal processing method and the MAC mechanism proposed in these studies made communication on POCs realistic, they did not investigate how to access POCs when multiple nodes want to communicate.

Leveraging POCs to realize both intra- and inter-coalition communication in UAV swarms is a feasible way when considering both the switching cost and the payload constraint. However, since POCs incur adjacent-channel interference as well, as was mentioned above, the channel access for each coalition should be well designed. As far as we are concerned, no similar work has been done before which jointly considered the forwarding function and the adjacent-channel interference incurrence of POCs.

3 System model and problem formulation

3.1 Scenario description

Consider a UAV swarm is executing a search task where one or more stationary targets exist in a certain area and UAVs need to find them out. The area is divided into several grid cells, and each target lies in at most one cell. A total of N UAVs are grouped into H coalitions for execution. Each coalition is a work unit and is composed of one head and several members. The members are in charge of detecting the area flying over and each of them is equipped with a surveillance sensor [3]. The trajectory of each coalition is designed in advance and each UAV is equipped with a navigation sensor for present position. Let $\mathcal{H} = \{1, \ldots, H\}$ denote the set of heads and coalition h denote the coalition led by head $h \in \mathcal{H}$. Let $\mathcal{M}$ denote the set of all members and $\mathcal{M}_h$ denote the set of members in coalition h. Note that, each UAV is supposed to belong to one coalition and different coalitions consist exactly different UAVs, i.e., $\bigcup_{h=1}^{H} \mathcal{M}_h = \mathcal{M}$ and $\mathcal{M}_{h_1} \cap \mathcal{M}_{h_2} = \phi, \forall h_1, h_2 \in \mathcal{H}$.

In the task, coalition heads are responsible for finding out all the targets. Each head maintains an individual cognitive map where each grid cell has a probability that a target is present in it [3]. However, owing to different trajectories and the existence of false alarm and missing detection, the map of each coalition differs from one another. Therefore, to finish the task faster and better, they tend to work in a cooperative way. Specifically, each head always maintains the latest measurement of itself. When two heads come into the communication range, they synchronize their measurements and update their local cognitive maps. When all targets are found out, i.e., for each target, the existing probability of it exceeds a threshold in at least one cognitive map, the task terminates. Suppose the whole task will be executed for T stages and define the set of stages as $\mathcal{T} = \{1, \ldots, T\}$.

An example of the scenario is given in Figure 1, and an illustration of the whole execution process is given in Figure 2. Specifically, every time when the UAV swarm reaches a new spot, coalition members detect the current area and coalition heads decide channels for communication. Then the members upload the messages to their corresponding heads on selected channels. After that, heads will make a fusion [26] and exchange the fused messages with their adjacent coalition heads. Finally, heads make map updates[1)].

3.2 Channel model

When utilizing orthogonal channels, communication can only be realized when the transmitter and the receiver operate on the same channel. Different from that, utilizing POCs allows the transmitter and

1) This paper focuses on the communication problem during the execution process while others, e.g., the dynamics and the information fusion, are beyond the scope.

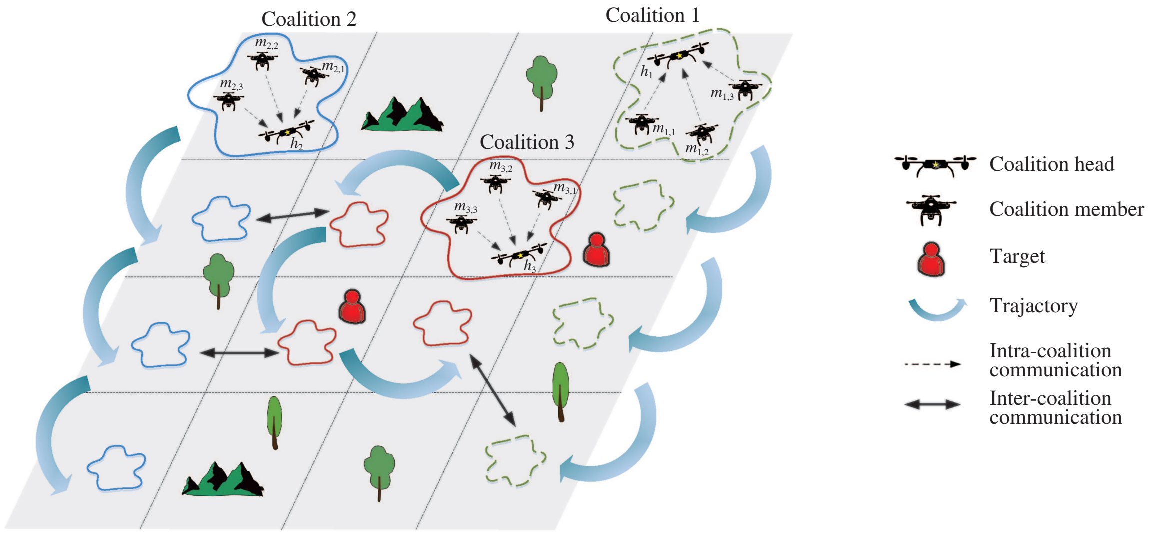

Figure 1 (Color online) Illustration of a search task.

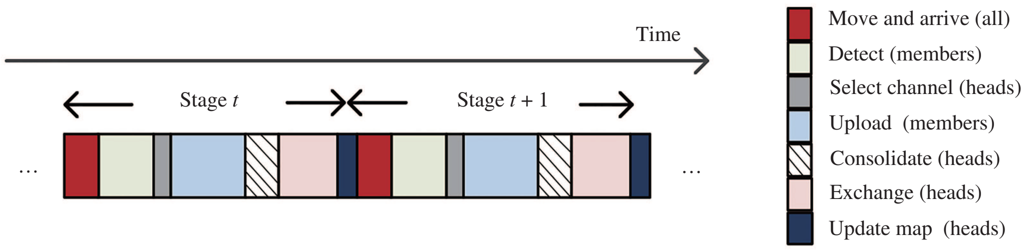

Figure 2 (Color online) The illustration of executing the task in time domain.

the receiver to operate on different channels if they are overlapped and therefore the switching cost for multiple communication can be reduced. The feasibility of such communication method has been validated in [28, 29] and is leveraged in this paper.

Communication links among UAVs, i.e., air-to-air (A2A) links, are supposed to be line-of-sight (LOS) in this paper [19, 47]. Without loss of generality, consider a pair of UAVs, x and y, in the network, where x is the transmitter and y is the receiver. Let p_{xy} denote the received signal strength of y from x. It is influenced by two factors, the physical distance and the channel distance [48].

To investigate the impact of the physical distance, we first suppose x and y operate on the same channel. Define the physical distance between x and y as d_{xy}. The path loss model is adopted as $L_{xy} = \Theta_{xy} + \eta_{\mathrm{LOS}}$, where η_{LOS} is an additional attenuation factor for LOS links [47] and Θ_{xy} is expressed as

$$\Theta_{xy}\,(\mathrm{dB}) = 20\log_{10}(d_{xy}) + 20\log_{10}(f_c) + 10\log_{10}\left[\left(\frac{4\pi}{c}\right)^2\right], \tag{1}$$

where f_c is the carrier frequency and c is the speed of light. Accordingly, the channel gain between x and y is $\varsigma_{x\to y} = 10^{-L_{xy}/10}$. When the transmission power of x is p_x, the received signal strength of y is $p_{xy} = p_x \cdot \varsigma_{x\to y}$.

However, when the transmitter and the receiver operate on different channels, the channel distance will also influence the signal strength of the receiver. Suppose the bandwidth of each channel is B and the frequency separation of adjacent channels is f_τ. Define the channel set as $\mathcal{A} = \{1, \ldots, A\}$ and the channel selections of x and y as a_x and a_y, which correspond to the central frequencies as f_x and f_y respectively. Consider an idealized discrete model where the power distribution of the transmitted signal, the transmit spectrum mask and the receiver filter response have exactly the same form $S(f)$ [48]. In this way, an overlapping factor which captures the amount of overlap between the transmission on a_x

and the reception on a_y can be expressed as

$$H_{xy}\left(a_x, a_y\right)=\frac{\int_{-\infty}^{-\infty} S\left(f\right)\cdot S\left(f-\delta_{xy}\right)\mathrm{d}f}{\int_{-\infty}^{-\infty} S\left(f\right)\cdot S\left(f\right)\mathrm{d}f}, \tag{2}$$

where $\delta_{xy}=|f_x-f_y|=f_\tau\cdot|a_x-a_y|$.

It can be seen that, when δ_{xy} is large enough, $H_{xy}=0$, signals from a_x will not be received on a_y and they are orthogonal channels. Otherwise, if $a_x\neq a_y$, they will be overlapped to some extent, i.e., POCs, and the receiver working on a_y can receive signals from a_x if the signal-to-interference-ratio (SINR) exceeds a threshold p_τ.

Considering the comprehensive impact of both the physical distance and the channel distance, the received signal strength of y from x can be expressed as $p_{xy}=p_x\cdot\varsigma_{x\to y}\cdot H_{xy}$.

3.3 Communication processes

As was mentioned before, the communication process during the mission can be divided into two periods. The first period (Period I) is the intra-coalition communication where members upload their sensed messages to the corresponding heads. The second period (Period II) is the inter-coalition communication where coalition heads exchange messages with neighboring ones. This period will be entered when coalition heads finish fusing the messages collected in Period I. The communication of the two periods in detail are given below.

Define the length of Period I as T_1. During this period, the uploading in a specific coalition can be scheduled by the head but the process is executed in all coalitions simultaneously. This means, intra-coalition interference does not exist but inter-coalition interference may happen because of the not far apart physical or channel distances of adjacent coalitions.

Define the kth member of coalition h as $m_{h,k}$, the path loss between $m_{h,k}$ and head h as $\varsigma_{h,k\to h}$ and the uploading power of each member in coalition h is P_h^{intra}. To make the intra-coalition communication more effective, all members in the same coalition are supposed to operate on the same channel with their head. Accordingly, the throughput of $m_{h,k}$ to its head h at a specific stage t can be expressed as

$$R_{h,k}^{\mathrm{intra}(t)}\left(a_h^{(t)},\boldsymbol{a}_{\mathcal{J}_h^{(t)}}^{(t)}\right)=B\cdot\log\left(1+\frac{P_h^{\mathrm{intra}}\varsigma_{h,k\to h}}{N_0+\sum_{g\in\mathcal{J}_h^{(t)}} I_{gh}^{(t)}}\right), \tag{3}$$

where B is the bandwidth, N_0 is the background noise, $I_{gh}^{(t)}$ is the interference resulted from current neighboring coalition g. Note that, $\mathcal{J}_h^{(t)}$ is the set of current neighbors of coalition h, which is defined according to the physical distance. Interference coming from non-neighboring coalitions is ignored, which is a widely used assumption in many existing studies [9, 26, 49]. Since coalition h and g may work on different channels, mutual interference not only depends on the path loss $\varsigma_{g\to h}^{(t)}$, but will also be influenced by the channel overlapping degree $H_{gh}^{(t)}$. Therefore,

$$I_{gh}^{(t)}\left(a_h^{(t)},a_g^{(t)}\right)=P_g^{\mathrm{intra}}\varsigma_{g\to h}^{(t)}H_{gh}^{(t)},\quad \forall g\in\mathcal{J}_h^{(t)}. \tag{4}$$

Suppose members in the same coalition are scheduled with equal time. The length of messages member $m_{h,k}$ uploads is

$$L_{h,k}^{\mathrm{u}(t)}\left(a_h^{(t)},\boldsymbol{a}_{\mathcal{J}_h^{(t)}}^{(t)}\right)=\frac{T_1}{|\mathcal{M}_h|}\cdot R_{h,k}^{\mathrm{intra}(t)} \tag{5}$$

and the length of messages coalition head h collects is

$$L_h^{\mathrm{c}(t)}\left(a_h^{(t)},\boldsymbol{a}_{\mathcal{J}_h^{(t)}}^{(t)}\right)=\sum_{k\in\mathcal{M}_h} L_{h,k}^{\mathrm{u}(t)}. \tag{6}$$

If the fusing ability of head h is depicted by its fusing coefficient λ_h, it will have a length of

$$L_h^{1(t)}\left(a_h^{(t)},\boldsymbol{a}_{\mathcal{J}_h^{(t)}}^{(t)}\right)=\lambda_h\cdot L_h^{\mathrm{c}(t)} \tag{7}$$

messages to exchange in the second period.

During Period II, to make more messages exchanged, each coalition head will have a dedicated time T_2 for broadcasting[2)] and no mutual interference exists. To avoid channel switching cost, suppose the working channel of each coalition in Period II remains unchanged with Period I. This means the transmitter and the receiver may work on POCs.

Define the path loss between head h and its neighbor head g at stage t as $\varsigma_{h\to g}^{(t)}$. If the broadcasting power of head h is P_h^{inter}, the current throughput from h to g can be expressed as

$$R_{h,g}^{\text{inter}(t)}\left(a_h^{(t)},a_g^{(t)}\right)=B\cdot\log\left(1+\frac{P_h^{\text{inter}}\varsigma_{h\to g}^{(t)}H_{hg}^{(t)}}{N_0}\right),\quad \forall g\in\mathcal{J}_h^{(t)}, \tag{8}$$

where B, N_0 and H_{hg} are the same parameters in Period I. In this way, the length of message head g receives from head h is

$$L_{h,g}^{2(t)}\left(a_h^{(t)},a_g^{(t)}\right)=T_2\cdot R_{h,g}^{\text{inter}(t)},\quad \forall g\in\mathcal{J}_h^{(t)}. \tag{9}$$

The length of message head h broadcasts depends on the minimum amount of messages received by all its neighbors. Mathematically,

$$L_h^{2(t)}\left(a_h^{(t)},\boldsymbol{a}_{\mathcal{J}_h^{(t)}}^{(t)}\right)=\min_{g\in\mathcal{J}_h^{(t)}}L_{h,g}^{2(t)}. \tag{10}$$

Note that, UAVs in these two periods are supposed to be relatively static since moving around not only requires much energy but also results in poor communication quality. Moreover, since the two communication periods are both based on contention-free mechanism, the delay is controlled and the time constraint of the task can be satisfied.

3.4 Problem formulation

Because of the limited time or low throughput, each coalition member may not be able to empty its sensed messages in Period I, i.e., $L_{h,k}^{\text{u}(t)}\leqslant L_{h,k}^{\text{s}(t)},\forall h\in\mathcal{H},\forall k\in\mathcal{M}_h,\forall t\in\mathcal{T}$, where $L_{h,k}^{\text{s}(t)}$ is the length of messages $m_{h,k}$ sensed in stage t. Note that, considering the limited storage of coalition members, the messages which cannot be uploaded will be emptied in each stage. In the second period, the coalition heads may not be able to empty their messages as well, i.e., $L_h^{2(t)}\leqslant L_h^{1(t)},\forall h\in\mathcal{H},\forall t\in\mathcal{T}$. Specifically, if a coalition is isolated from others, i.e., it cannot communicate with any others, it will not make an exchange, i.e., $L_h^{2(t)}=0,\forall h\in\mathcal{H},\forall t\in\mathcal{T}$. Suppose coalition heads have enough storage and the messages which cannot be exchanged will be stored. Therefore, in stage t, the length of messages remaining to be sent by head h is

$$L_h^{\text{b}(t)}\left(a_h^{(1)},\ldots,a_h^{(t)},\boldsymbol{a}_{\mathcal{J}_h^{(1)}}^{(1)},\ldots,\boldsymbol{a}_{\mathcal{J}_h^{(t)}}^{(t)}\right)=L_h^{\text{b}(t-1)}-L_h^{2(t-1)}+L_h^{1(t)}. \tag{11}$$

Define the efficiency of the communication process of coalition h in stage t as

$$\eta_h^{(t)}\left(a_h^{(1)},\ldots,a_h^{(t)},\boldsymbol{a}_{\mathcal{J}_h^{(1)}}^{(1)},\ldots,\boldsymbol{a}_{\mathcal{J}_h^{(t)}}^{(t)}\right)=\frac{L_h^{\text{c}(t)}}{\sum_{k\in\mathcal{M}_h}L_{h,k}^{\text{s}(t)}}+\frac{L_h^{2(t)}}{L_h^{\text{b}(t)}}. \tag{12}$$

It can be seen that the efficiency consists of two parts, which correspond to Periods I and II respectively. On the right-hand side of (12), the first item is the ratio between the length of collected messages of the coalition head and the length of total sensed messages of all members, while the second item is the ratio between the length of broadcasted messages of the coalition head and the messages it stores. Note that, larger $\frac{L_h^{\text{c}(t)}}{\sum_{k\in\mathcal{M}_h}L_{h,k}^{\text{s}(t)}}$ indicates that more messages are uploaded by coalition members and the uploading efficiency is higher. Meanwhile, larger $\frac{L_h^{2(t)}}{L_h^{\text{b}(t)}}$ indicates that more backlogged messages are broadcasted and the exchange efficiency is higher.

2) One or more coalition heads can broadcast simultaneously and many MAC protocols can be utilized, such as time division multiple access (TDMA) and spatial reused TDMA [50].

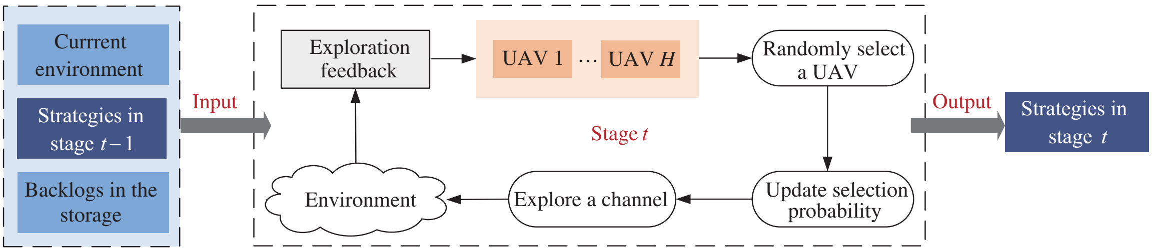

Figure 3 (Color online) An illustration of the proposed algorithm.

Therefore, the problem can be formulated as maximizing the efficiency of all coalitions during the whole mission by optimizing the POC access. Mathematically,

$$\mathrm{P}: \quad (\boldsymbol{a}_1^*, \ldots, \boldsymbol{a}_H^*) = \arg\max \sum_{t\in\mathcal{T}} \sum_{h\in\mathcal{H}} \eta_h^{(t)} = \arg\max\left(\eta_1 + \eta_2\right), \tag{13}$$

where $\boldsymbol{a}_h^* = \{a_h^{(1)*}, \ldots, a_h^{(T)*}\}, \forall h \in \mathcal{H}$, $\eta_1 = \sum_{t\in\mathcal{T}} \sum_{h\in\mathcal{H}} \frac{L_h^{\mathrm{c}(t)}}{\sum_{k\in\mathcal{M}_h} L_{h,k}^{\mathrm{s}(t)}}$ and $\eta_2 = \sum_{t\in\mathcal{T}} \sum_{h\in\mathcal{H}} \frac{L_h^{2(t)}}{L_h^{\mathrm{b}(t)}}$.

It can be seen that P is a combinatorial optimization problem and is therefore NP-hard. Using traditional optimization methods, e.g., convex optimization [23], to find the optimal solution to the problem results in huge computation complexity, especially when the number of coalitions or stages is large. Therefore, it is necessary to find a method with low-complexity.

4 Distributed online learning algorithm

To cope with the huge computation complexity resulted from the coupled relationship of multi-stage and multi-user, a decoupled method with low-complexity is required. Fortunately, machine learning is an effective way to solve the combinatorial optimization problem [17, 51] where players update strategies repeatedly and individually using the history trial and feedback information.

While many learning algorithms, e.g., the best response [30, 31], the stochastic learning automata [32], have been proposed to solve problems in a distributed way, they are not guaranteed to find an optimal solution. Therefore, motivated by [49], a multi-stage SAP based learning algorithm is proposed. Specifically, in each stage, the current environment, strategies of the previous stage and the current backlogged messages will be the input of the learning process and the strategies of the current stage will be the output. For the learning process, during each iteration, one UAV is selected randomly to update its channel selection probability and then to explore a channel accordingly. The feedback will be given to UAVs when the explored action works in the environment. The process of the learning algorithm is shown in Figure 3. Compared with traditional optimization methods which require a centralized computing unit, the proposed algorithm reduces the computation complexity since the problem is solved in a distributed way.

4.1 Algorithm description

The proposed algorithm will be executed by coalition heads in each stage since the environment changes. During the initialization, each coalition head selects one of the POCs randomly for the first stage while adheres to the current channel for the rest of the stages. During the updating process, in each iteration, one coalition head will be selected for updating while others' strategies remain unchanged. The selected head h (updater) considers both its own and the neighboring coalitions' efficiency. This is motivated by the local altruistic model proposed in [49] and it has been shown that this model performs better than those only considering individual benefit. The updater refreshes the channel selection probability according to (14), where $p_h^a(k)$ is the probability that it will select channel $a, \forall a \in \mathcal{A}$. In the kth iteration, β is the learning parameter, $\boldsymbol{a}_{-h}$ is the strategy set of all the other players except h and $u_h = \eta_h + \sum_{n\in\mathcal{J}_h} \eta_n$ is the utility it obtains if it chooses channel a while others maintain their strategies. Note that, the learning parameter β plays an important role in this update rule, which is the tradeoff between exploration and exploitation. Specifically, smaller β implies that each action has a similar probability and the updater is willing to explore. An extreme case is when $\beta = 0$, all actions have the same probability $\frac{1}{|\mathcal{A}|}$ and the updater chooses an action randomly. Meanwhile, larger β ensures the action which can bring in higher utility has higher probability and the updater tends to choose the best response action. Therefore, it is advisable that β is small at the beginning and turns larger as the algorithm iterates [52]. The whole process is described in Algorithm 1.

Algorithm 1 Multi-stage SAP-based learning algorithm

At the beginning of stage $t, 1 \leqslant t \leqslant T$, UAVs move to the pre-defined position. The initialization and the updating process will be executed in every stage. Define the final strategy of stage t $(1 \leqslant t \leqslant T-1)$, as $\boldsymbol{a}^t = \{a_1^t, \ldots, a_H^t\}$.

Initialization: Set iteration $k = 0$. The coalition heads obtain the knowledge of the current environment. Coalition head $h, \forall h \in \mathcal{H}$, sets the channel selection probability as $p_h^a(0) = \frac{1}{|\mathcal{A}|}, \forall a \in \mathcal{A}$. If it is the first stage, i.e., $t = 1$, it selects a channel $a_h(0)$ randomly. Otherwise, it maintains its current channel, i.e., $a_h(0) = a_h^{t-1}$.

Updating:

Loop $k = 1, 2, \ldots, K_{\max}$ (the maximum iteration step).

1. One coalition head h is selected randomly to update while others' strategies remain unchanged, i.e., $\boldsymbol{a}_{-h}(k) = \boldsymbol{a}_{-h}(k-1)$.

2. The updater h refreshes the selection probability according to the following rule:

$$p_h^a(k) = \frac{\exp\{\beta \cdot u_h[a, \boldsymbol{a}_{-h}(k)]\}}{\sum_{a \in \mathcal{A}} \exp\{\beta \cdot u_h[a, \boldsymbol{a}_{-h}(k)]\}}. \tag{14}$$

3. The updater h selects a channel according to the probability and broadcasts to its adjacent coalition heads.

End loop

4.2 Algorithm analysis

Whether the proposed algorithm can converge to the optimum should be analyzed. Game theory is a powerful and widely-applied mathematical tool to formulate problems when strategies of multi-users are coupled [32, 53]. Therefore, we resort to it to make analysis of the algorithm.

Owing to the coupled relationship of players and stages, the POC access problem is formulated into several stage-based game models. Specifically, in stage t, the game is denoted as

$$\mathcal{G}(t) = \left\{\mathcal{H}, \mathcal{A}, \{\mathcal{J}_h(i)\}_{\forall h \in \mathcal{H}, 1 \leqslant i \leqslant t}, \{a_h(i)\}_{\forall h \in \mathcal{H}, 1 \leqslant i \leqslant t}, \{u_h(t)\}_{\forall h \in \mathcal{H}}\right\}, \tag{15}$$

where $\mathcal{H}$ is the set of players (coalition heads), $\mathcal{A}$ is the set of POCs, $\mathcal{J}_h(i)$ and $a_h(i)$ are the set of neighbors and the channel selection of player h in stage i, $u_h(t)$ is the utility of player h in the present stage. Note that, for each player, it will not only aim at maximizing its own efficiency, but will also consider its neighboring players'. Therefore, the utility function of player h in stage t is designed as

$$u_h(t) = \eta_h^{(t)} + \sum_{n \in \mathcal{J}_h(t)} \eta_n^{(t)}. \tag{16}$$

Since the current utility not only depends on the current strategy and neighbors but will also be affected by the strategies executed in the former stages and former neighbors, the game is expressed as

$$\mathcal{G}(t): \max_{a_h(t) \in \mathcal{A}} u_h\left(a_h(t), \boldsymbol{a}_{\mathcal{J}_h(t)}(t) \middle| \boldsymbol{x}(t)\right), \quad \forall h \in \mathcal{H}, \tag{17}$$

where

$$\boldsymbol{x}(t) = \left\{\underbrace{a_h(1), \ldots, a_h(t-1)}_{\text{history strategies}}, \underbrace{\boldsymbol{a}_{\mathcal{J}_h(1)}(1), \ldots, \boldsymbol{a}_{\mathcal{J}_h(t)}(t)}_{\text{history strategies of neighbors}}\right\}$$

is the set of history strategies.

Definition 1. A game is an exact potential game (EPG) if the following equation holds [54]:

$$u_h(\overline{a}_h, \boldsymbol{a}_{-h}) - u_h(a_h, \boldsymbol{a}_{-h}) = \phi(\overline{a}_h, \boldsymbol{a}_{-h}) - \phi(a_h, \boldsymbol{a}_{-h}), \quad \forall h \in \mathcal{H}, \quad \overline{a}_h, a_h \in \mathcal{A}, \quad \overline{a}_h \neq a_h, \tag{18}$$

where ϕ is its exact potential function.

Lemma 1. For any stage t, the proposed game $\mathcal{G}(t)$ is an exact potential game.

Proof. To prove $\mathcal{G}(t)$ be an EPG, a potential function satisfying (18) should be found out. Design the potential function as

$$\phi(t) = \sum_{h \in \mathcal{H}} \eta_h(t). \tag{19}$$

For simplicity of expression, the utility function of player h is written as $u_h\left[a_h, \boldsymbol{a}_{\mathcal{J}_h} | \boldsymbol{x}\right]$, where t is omitted. When any player h changes its strategy from a_h to $\overline{a}_h$ in stage t, the deviations of its utility function and the potential function are

$$\Delta u_h = \left[\eta_h\left(\overline{a}_h, \boldsymbol{a}_{\mathcal{J}_h}\right) + \sum_{n\in\mathcal{J}_h} \eta_n\left(a_n, \overline{\boldsymbol{a}}_{\mathcal{J}_n}\right)\right] - \left[\eta_h\left(a_h, \boldsymbol{a}_{\mathcal{J}_h}\right) + \sum_{n\in\mathcal{J}_h} \eta_n\left(a_n, \boldsymbol{a}_{\mathcal{J}_n}\right)\right], \tag{20}$$

$$\begin{aligned}\Delta\phi = &\left[\eta_h\left(\overline{a}_h, \boldsymbol{a}_{\mathcal{J}_h}\right) + \sum_{n\in\mathcal{J}_h} \eta_n\left(a_n, \overline{\boldsymbol{a}}_{\mathcal{J}_n}\right) + \sum_{n\in\{\mathcal{H}/\mathcal{J}_h\}} \eta_n\left(a_n, \boldsymbol{a}_{\mathcal{J}_n}\right)\right] \\ &- \left[\eta_h\left(a_h, \boldsymbol{a}_{\mathcal{J}_h}\right) + \sum_{n\in\mathcal{J}_h} \eta_n\left(a_n, \boldsymbol{a}_{\mathcal{J}_n}\right) + \sum_{n\in\{\mathcal{H}/\mathcal{J}_h\}} \eta_n\left(a_n, \boldsymbol{a}_{\mathcal{J}_n}\right)\right] \\ = &\left[\eta_h\left(\overline{a}_h, \boldsymbol{a}_{\mathcal{J}_h}\right) + \sum_{n\in\mathcal{J}_h} \eta_n\left(a_n, \overline{\boldsymbol{a}}_{\mathcal{J}_n}\right)\right] - \left[\eta_h\left(a_h, \boldsymbol{a}_{\mathcal{J}_h}\right) + \sum_{n\in\mathcal{J}_h} \eta_n\left(a_n, \boldsymbol{a}_{\mathcal{J}_n}\right)\right].\end{aligned} \tag{21}$$

It can be seen that, $\Delta u_h = \Delta\phi, \forall h \in \mathcal{H}$. This completes the proof.

Theorem 1. When the learning parameter β is sufficiently large, the algorithm will converge to the optimal solution in each stage asymptotically.

Proof. The proof of this theorem follows the idea of [49]. Based on the knowledge of the discrete Markov process, it can be deduced that, in an exact potential game, the stable probability that any strategy profile $\boldsymbol{a}$ can be converged to is $\mu(\boldsymbol{a}) = \frac{\exp\{\beta\phi(\boldsymbol{a})\}}{\sum_{\boldsymbol{a}'\in\mathcal{A}}\beta\phi(\boldsymbol{a}')}$, where ϕ is the potential function of the game.

In a specific stage, suppose a total of K strategy profiles can maximize the potential function and define the set of them as $\boldsymbol{a}^* = \{\boldsymbol{a}_1^*, \ldots, \boldsymbol{a}_K^*\}$. When β is sufficiently large, the following inequality holds:

$$\exp\left\{\beta\phi\left(\boldsymbol{a}_k{}^*\right)\right\} \gg \exp\left\{\beta\phi\left(\boldsymbol{a}\right)\right\}, \quad \forall \boldsymbol{a}_k{}^* \subseteq \boldsymbol{a}^*, \quad \forall \boldsymbol{a} \subseteq \left\{\mathcal{A}/\boldsymbol{a}^*\right\}. \tag{22}$$

Accordingly, $\lim_{\beta\to\infty}\sum_{k=1}^{K}\mu\left(\boldsymbol{a}_k^*\right) = 1$. This means, the aggregate probability over all optimal strategy profiles will approach one asymptotically.

Meanwhile, since the potential function is consistent with the optimization object of each state, the algorithm can asymptotically reach the optimal solution as well. This completes the proof.

Some discussion about the proposed algorithm are given below.

• The algorithm is online which will be executed by coalition heads at each stage. This means the channel access solution does not need to be pre-planned before the search mission starts. Therefore, the UAV swarm can perform better when encounter varying environment or emergencies since they can make dynamic and adaptive strategies.

• The algorithm is distributed and is efficient in large-scale networks. Since the algorithm is executed by each coalition head, the computation complexity is reduced to a great extent compared with traditional optimization method. Specifically, the computation complexity of the proposed algorithm is obtained as follows. The updater selection process has a complexity of $\mathcal{O}(C1)$, where $C1$ is a small constant. The updating process involves A addition and A division operations and has a complexity of $A\cdot\mathcal{O}(C2)$, where A is the number of channels and $C2$ is a small constant. Accordingly, the total complexity of the proposed algorithm is $\mathcal{T} = K_{\max}\cdot(\mathcal{O}(C1) + A\cdot\mathcal{O}(C2))$, where $K_{\max}$ is the number of iterations. It can be seen that the complexity scales with the channel amount instead of the number of coalitions.

• In most cases, the learning parameter β increases with the number of iterations. This helps the updater explore new strategies in the early period and exploit the best strategy in the later period. Such updating rule makes the algorithm not be trapped in local optimal solutions and achieve the global optimum asymptotically.

• Although the algorithm is executed for optimization in each individual stage, it can be seen from Figure 3 that the input of the learning process is relative with the strategies in the previous stage, which means that the coupled relationship among stages is considered. In addition, it is proved in Theorem 1 that the algorithm converges to the optimum asymptotically in each stage. Therefore, it can be expected that the algorithm can achieve a nice result of problem P.

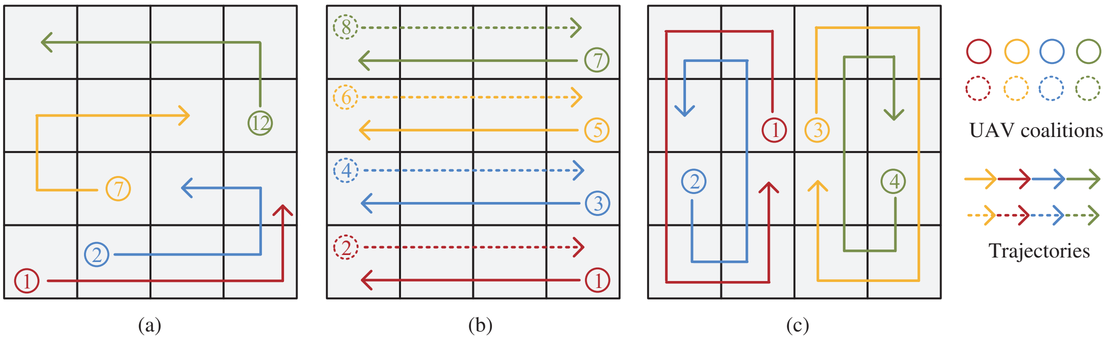

Figure 4 (Color online) An illustration of the proposed three trajectories. (a) Carpet; (b) Troop; (c) Ring.

5 Simulation results and discussion

This section gives and discusses the simulation results. The basic simulation parameters are as follows. The mission area is a 12000 m $\times$ 12000 m square. The amount of POCs is 6, the bandwidth of each channel is 22 MHz and the separation of adjacent channels is 5 MHz. The transmission power of coalition members and heads are 20 dBm and 24.77 dBm respectively. The SNR threshold is $p_\tau = -4$ dB. When the physical distance of two coalition heads is less than 4.1953×10^3 m, they are defined as neighbors. The speed of light is $c = 3 \times 10^8$ m/s. The carrier frequency is $f_c = 2.4 \times 10^9$ Hz. The additional attenuation factor is $\eta_{\rm LOS} = 5$ dB. The background noise is $N_0 = -90$ dBm. Each coalition has eight members and the length of messages sensed by each member is 1024×10^3 bit. The fusing ability of all coalition heads is configured as one. Most parameters are referred to [47].

5.1 Scenario settings

To investigate the universality and the effectiveness of the proposed method, three representative settings are constructed for the given area, as is shown in Figure 4. The first one is named as Carpet, where the number of coalitions and stages are 12 and 5, respectively. Except the first and the last grid cells, each grid cell will be detected by at least two different coalitions. The second one is named as Troop, where the number of coalitions and stages are 8 and 4 respectively. Each coalition moves straightly and each grid cell is detected by the same two coalitions. The third one is named as Ring, where the number of coalitions and stages are 4 and 8 respectively. Each two coalitions are in charge of half the area and the trajectory of each coalition forms a ring.

Because of the different number of coalitions and trajectories, the density of the three networks varies. Specifically, the Carpet has the largest density where each coalition has an average of 2.75 adjacent coalitions in each stage while the Ring has the smallest density where each coalition has at most one adjacent coalition in each stage. This has an impact on the degree of mutual interference in Period I and the number of backlogged after Period II. It can be seen from the results presented later that the proposed method achieves higher efficiency in many cases under the three settings and we believe that it can be applied in other networks as well.

5.2 Convergence performance

The convergence performance of the proposed algorithm is validated first. The learning parameter is set as $\beta = 1.2 \times i$, where i is the iteration time. We make simulations under the three settings when $T_1 = 0.25$ s and $T_2 = 0.35$ s and the results are the average of 100 independent simulations. To demonstrate the effectiveness of the proposed algorithm, we make a comparison with the best response (BR) algorithm. In BR, the updater in each iteration selects the optimal strategy which maximizes its current utility. Such a greedy rule makes the algorithm simple and has been widely used [30, 31].

It can be seen from Figure 5 that the algorithm can always converge and the result is better than that obtained by the BR algorithm in the Carpet and the Troop settings. This is because BR may be trapped in the suboptimum while SAP can reach the optimum with high probability. In the Ring setting, the two algorithms converge to almost the same result. This is because, the number of coalitions is small in this situation and the optimal solution is easy to be found out.

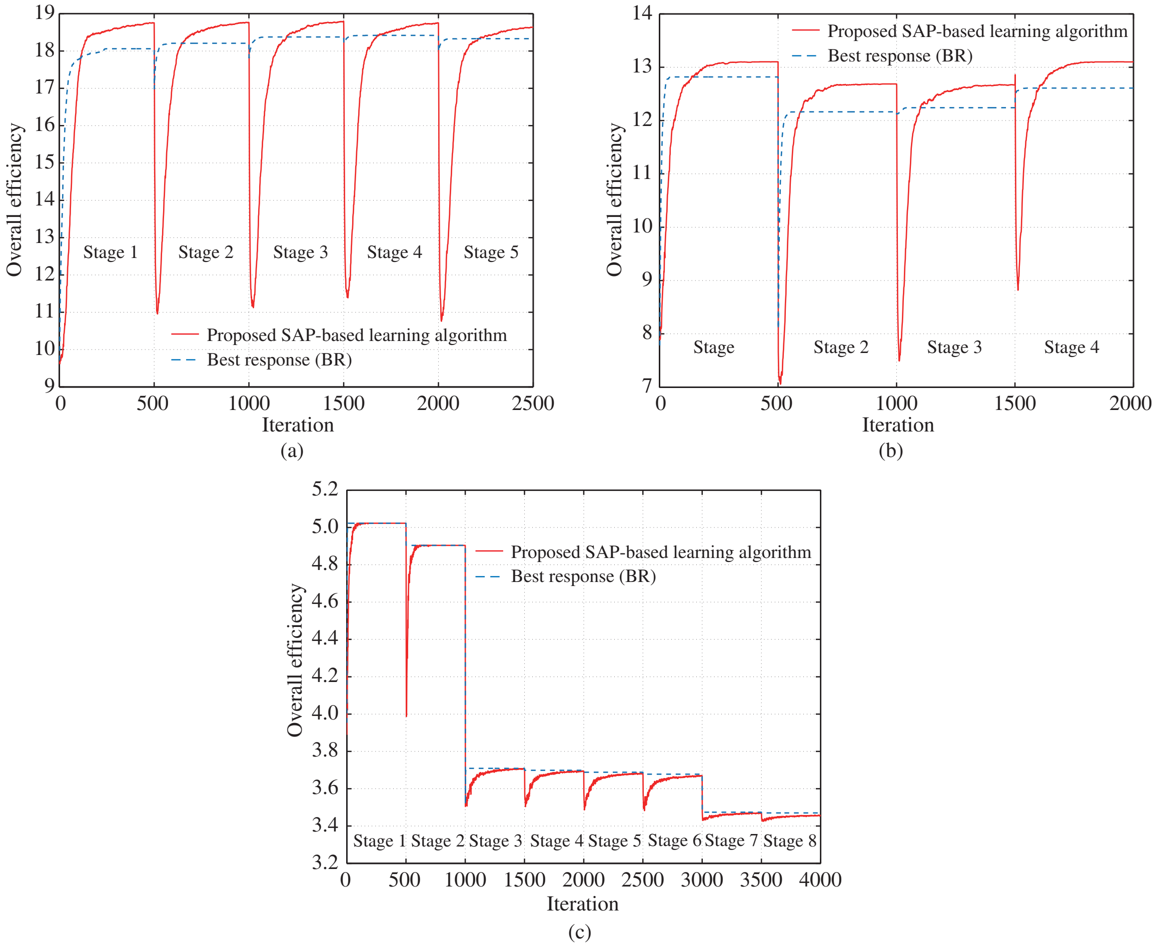

Figure 5 (Color online) The convergence behavior between SAP and BR under three settings. (a) Carpet; (b) Troop; (c) Ring

Then the effectiveness of the proposed method will be discussed. To avoid inter-coalition interference in Period I, it is better for adjacent coalitions using orthogonal channels. On the other hand, to make more messages transmitted during Period II, all coalitions tend to work on the same channel. Such a transmission method is named as orthogonal first and same later (OFSL) in this section. It can be seen that, this method requires UAVs to be equipped with two transceivers or to switch from time to time. Specifically, if each UAV has only one transceiver, it needs to switch twice during a specific stage. By comparison, when leveraging to POCs, each UAV only needs to switch at most once when entering a new stage. We make comparisons with OFSL under different settings and each result is an average of 100 simulations.

5.3 Influence of transmission power

The influence of the transmission power for inter-coalition communication is analyzed in this subsection. The result of the Carpet setting is given in Figure 6 for representative. It can be seen that, the overall efficiency rises with larger p^{inter}. This is because when p^{intra} is fixed, the amount of collected messages by coalition heads in Period I is the same. When p^{inter} turns larger, more messages in the storage can be broadcasted in Period II, which results in higher utility. It can also be seen that, when $p^{\text{inter}} = 23.01$ dBm, the converged overall efficiency in different stages shows a dropping trend which is not obvious in the other two cases. This may be because of the following two reasons. First, when p^{inter} is not large enough, coalition heads may need to work on adjacent channels, or even the same channel, to make message exchange. If their converged channel selection strategies are not satisfied, i.e., the SINR of the receiver cannot exceed the demodulation threshold, the exchange will be failed which makes $\eta_2 = 0$. Secondly, more storage will be backlogged with lower inter-coalition transmission power. This will make the overall efficiency decline continuously when the task execution goes on. However, although larger p^{inter} brings

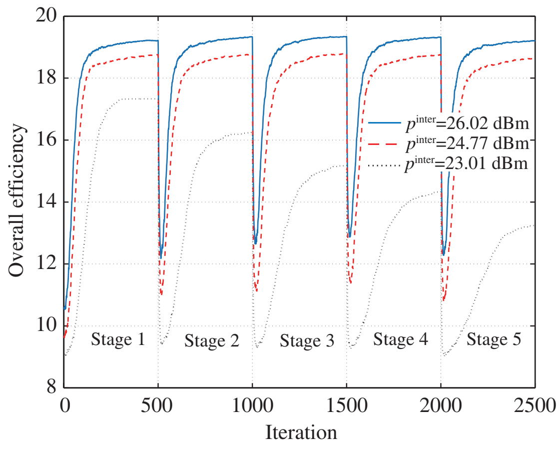

Figure 6 (Color online) The convergence behavior in Carpet with different intra-coalition transmission powers.

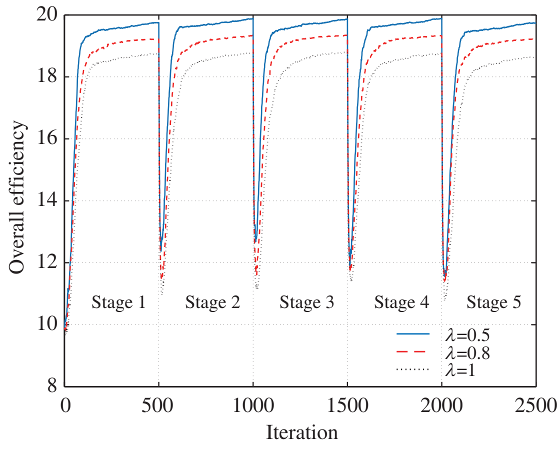

Figure 7 (Color online) The convergence behavior in Carpet with different fusion abilities.

in higher overall efficiency, the cost of energy should also be considered when choosing the transmission power of UAVs.

5.4 Influence of fusion ability

The influence of the fusion ability of coalition heads is analyzed in this subsection. The result of the Carpet setting is given in Figure 7 for representative. It can be seen that, when the heads have better fusion ability, i.e., lower fusing coefficient η, the overall efficiency will be higher. The result can be easily explained since the higher fusion ability, the fewer messages required to be exchanged. This eases the burden of coalition heads in Period II and can result in higher η_2. However, it should be noted that better fusion ability has a higher demand for the equipment. Therefore, there is a tradeoff between the overall efficiency and the hardware cost when producing UAVs.

5.5 Influence of uploading time

The influence of the uploading time in Period I, i.e., T_1, is analyzed in this subsection and the simulation results of the tree trajectories are given in Figure 8. We first analyze the results of the Carpet trajectory. It can be seen from Figure 8(a) that, when T_2 is fixed and T_1 turns larger, with the OFSL method, the overall efficiency increases first, drops later, then has a slight rising trend and stays unchanged finally. This is because at first, when T_1 turns larger, coalition members can upload more information, all of which can be broadcasted by coalition heads, bringing in higher η_1 and the same η_2. After that, although more information can still be uploaded with larger T_1, coalition heads cannot broadcast them all, resulting in heavier storage and lower η_2. Then, the amount of uploaded information approaches the maximum, making η_1 rise more slowly and the backlogged storage can be broadcasted gradually. Finally, all information can be uploaded, ensuring $\eta_1 = 1$, and the backlogged storage remains unchanged. By comparison, the rising trend of the proposed method has longer duration than OFSL. This is because POCs result in inter-coalition interference. Under the same T_1, the amount of uploaded messages in Period I will be fewer than those when utilizing orthogonal channels. Therefore, the storage can still be emptied by coalition heads in Period II even with larger T_1. After reaching a threshold, the uploaded messages will be backlogged and the overall efficiency decreases.

The results of the Troop trajectory have a similar trend with that of the Carpet trajectory. However, since the network topology in this situation is relatively sparser, mutual interference will be less severe in Period I when working on POCs. Therefore, under the same T_1, more messages can be uploaded and the backlog appears faster. This explains why the turning point of the red curve comes earlier in Figure 8(b) comparing with Figure 8(a).

The Ring trajectory shows different results with the other two. This is because the network is quite sparse in this situation, where each coalition has at most one adjacent coalition in each stage. Therefore, the amount of uploaded messages in Period I can be large even with small T_1. This brings in a rela-

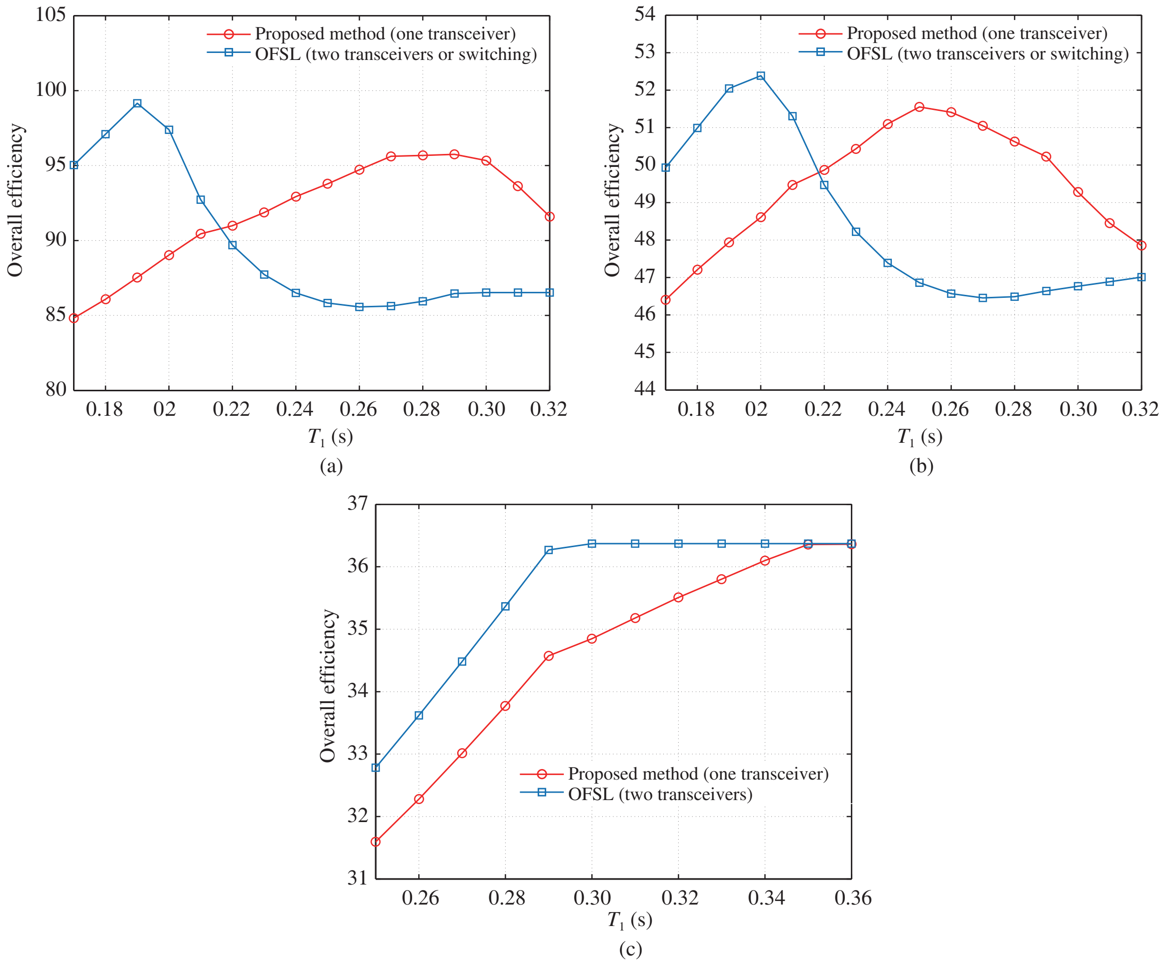

Figure 8 (Color online) The comparison between the proposed method and OFSL with $T_2 = 0.35$ s under three trajectories. (a) Carpet; (b) Troop; (c) Ring.

tively stable relationship with the amount of broadcasted messages in Period II and makes the curves in Figure 8(c) not up and down.

5.6 Influence of exchange time

The influence of the exchange time in Period II, i.e., T_2, is analyzed in this subsection and the simulation results of the tree trajectories are given in Figure 9. We first analyze the results of the Carpet trajectory. It can be seen from Figure 9(a) that, when T_1 is fixed and T_2 turns larger, the overall efficiency obtained by the OFSL method increases first and stays unchanged. This is because η_1 remains unchanged in this setting and more storage can be transmitted in Period II with longer T_2, resulting in larger η_2. However, when T_2 is large enough ($T_2 \geqslant 0.36$ s) for emptying all the storage, η_2 remains unchanged as well. On the other hand, the proposed method brings in a continuous rising overall efficiency. This is because the threshold has not been reached and more messages are transmitted with longer T_2, resulting in larger η_2.

The results of the other two trajectories are similar. Besides, it is notable that, in the Ring trajectory, the overall efficiency obtained by the proposed method approaches the result obtained by the OFSL method. This is because the sparse distribution results in little mutual interference. While ensuring enough uploaded messages in Period I, the coalitions may tend to work on the same channel for obtaining higher efficiency in Period II which produces a similar result of the OFSL strategy.

The discussion of the simulation results is given below:

• The proposed method can be applied in all the three representative settings. Since the settings have diverse densities, stages and trajectories, it is expected that the method can be applicable in other scenarios as well.

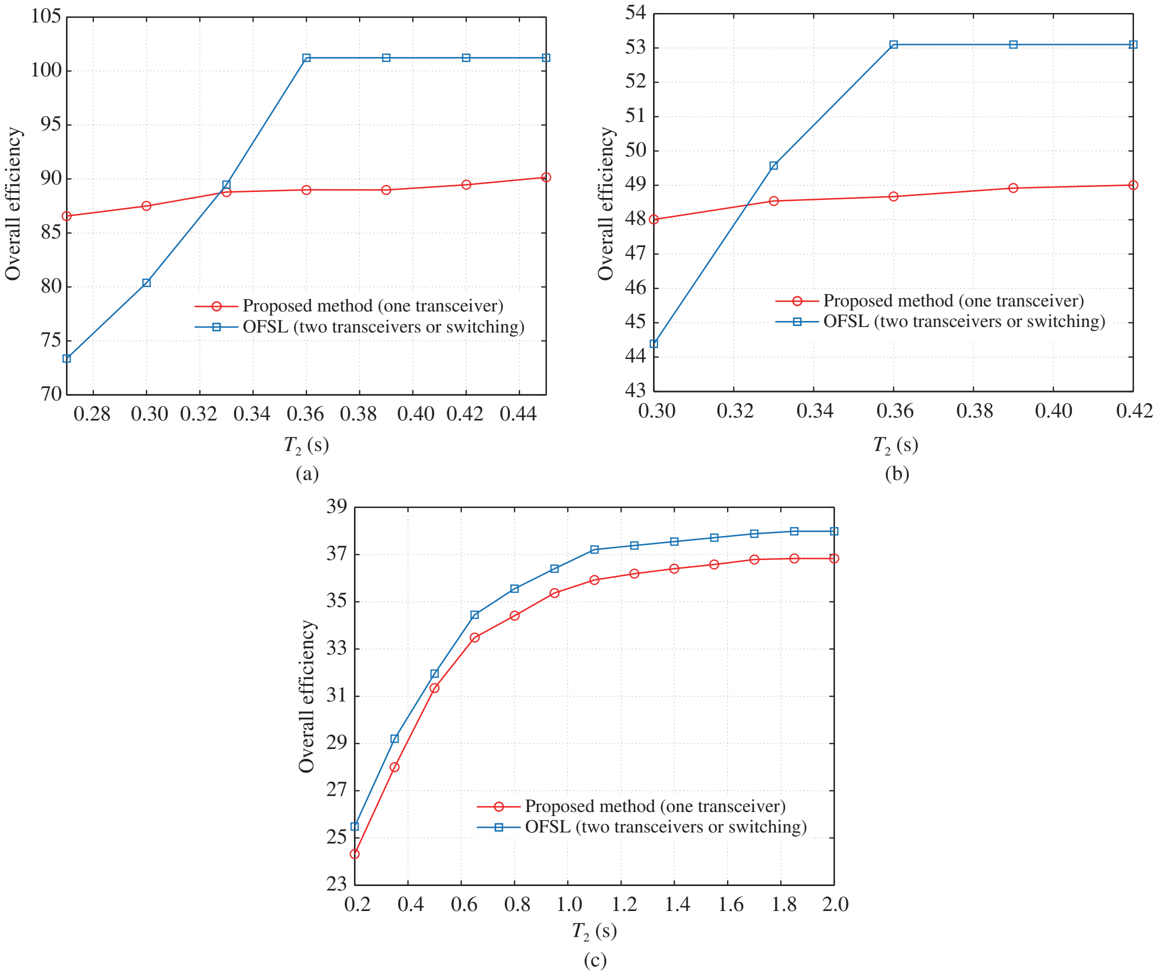

Figure 9 (Color online) The comparison between the proposed method and OFSL with $T_1 = 0.2$ s under three trajectories. (a) Carpet; (b) Troop; (c) Ring.

- By analyzing the numerical results presented in Figures 8 and 9, it is found that, in the best case, the proposed method can achieve 111.7% (Figure 8(a), $T_1 = 0.27$ s) and 118.2% (Figure 9(a), $T_2 = 0.27$ s) of the overall efficiency obtained by the OFSL method respectively. This means the method can be quite promising when the time parameter is designed properly.
- By comparison, in the worst case, the proposed method achieves 88.3% (Figure 8(a), $T_1 = 0.19$ s) and 87.9% (Figure 9(a), $T_2 = 0.36$ s) of the overall efficiency obtained by the OFSL method. However, it should be noted that the OFSL method requires two transceivers or channel switching, which is at the cost of hardware design and equipment.

6 Conclusion

This paper investigated the spectrum access problem in a coalition-based cooperative searching UAV swarm. To make both intra- and inter-coalition communication, UAVs may need to switch on different channels or to be equipped with multiple transceivers which will result in delays or hardware cost. Leveraging POCs can address this issue since they can forward messages on different channels. Therefore, a POC-based communication method was proposed in this paper. Because of the coupled relationship among the strategies of each coalition in each stage, the POC access problem is a combinatorial optimization one and an online learning algorithm was proposed to solve it. Specifically, the algorithm is distributed which will be executed by each coalition head in each stage and therefore can reduce the computation complexity. By resorting to the potential game theory, the algorithm was proved to converge to the optimum asymptotically in each stage. To validate the effectiveness of the proposed method, three representative settings were given and many simulations were made. According to the results, the proposed method can be applied in all the three settings and it is expected that it will be applicable in other scenarios as well.

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