Distributed Joint Channel-Slot Selection for Multi-UAV Networks: A Game-Theoretic Learning Approach

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Abstract. Unmanned aerial vehicle (UAV) has found promising applications in both military and civilian domains worldwide. In this article, we investigate the problem of distributed opportunistic spectrum access under the consideration of channel-slot selection simultaneously in multi-UAV networks from a game-theoretic perspective, and take into account the distinctive features of the multi-UAV network. We formulate the distributed joint channel-slot selection problem as a weighted interference minimization game. We prove that the formulated game is an exact potential game, and then use the distributed stochastic learning automata based joint channel and time slot selection algorithm to achieve the pure-strategy Nash equilibrium. The algorithm does not need information exchange among UAVs in the network which is more suitable for dynamic and practical enviroment. The simulation results demonstrate the effectiveness of the algorithm.

Keywords: Multi-UAV network · Joint channel-slot selection
Weighted interference minimization game
Potential game · Stochastic learning automata

1 Introduction

Unmanned aerial vehicle (UAV) has found promising applications in military areas and holds an important position in complex tactical offensive/defensive missions and natural security, such as surveillance and reconnaissance [1,2], information collection, etc. Meanwhile, its broad potential applications in the civilian domain have drawn great attention all over the world. It can be applied

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in many fields such as source seeking [3], target detection and localization [4], disaster sensing [5], communication coverage expansion [6].

With the development of technology, the multi-UAV network has been attached much attention to accomplish complex and dangerous tasks. The task of how to allocate scarce spectrum resource and mitigate the interference among the UAVs should be first addressed. Fortunately, opportunistic spectrum access (OSA) has been regarded as an efficient technology to deal with the spectrum shortage problem. Amount of research on OSA, e.g., [7–9], validates its effectiveness, therefore the solution can be applied in multi-UAV networks.

However, most existing research about OSA technology only studies either the channel resource or time slot resource. The limited spectrum resources can not meet the communication demands of large-scale multi-UAV network in the future, it is desirable to use time resource reasonably [10]. Therefore, the joint channel-slot selection scheme is one of the most powerful methods to solve the issues discussed above. Meanwhile, compared with the OSA systems in [7–9], there are several distinctive features of the multi-UAV network: (1) UAVs in the same cluster tend to choose the same channel when they have enough time slot resource; (2) considering the spatial locations of UAV clusters, the utility of the cluster is only affected by its nearby clusters, namely its neighbors; and (3) the experienced interference of UAV n can be divided into intra-cluster and inter-cluster interference, which represent the interference among UAVs belonging to the same cluster as UAV n and the neighboring clusters respectively.

The main contributions of this article are summarized as follows:

(1) We investigate the joint channel-slot selections of UAVs. Moreover, we distinguish intra-cluster and inter-cluster interference by formulating this problem as a weighted interference minimization game. The game is an exact potential game with at least one pure-strategy Nash equilibrium. Futhermore, this solution can minimize the aggregate interference level.
(2) In the distributed stochastic learning automata based joint channel and time slot selection algorithm, we consider the random payoff with the distinctive feature of multi-UAV network, e.g., UAVs in the same cluster choose the same channel when the slot resource is enough to suppress interference.

The remainder of this article is organized as follows. Section 2 discusses the system model and problem formulation. In Sect. 3, we formulate the weighted interference minimization game model and present theorem for the existence of NE. Then we use SLA based algorithm to achieve the optimum. Finally, simulation results for verifying the proposed game model are discussed in Sect. 4 while Sect. 5 contains the conclusion of this article plus some open issues for further work.

2 System Model and Problem Formulation

2.1 System Model

Consider a multi-UAV network involving N UAVs which belong to Q clusters. There are M channels and T time slots available for UAVs in each cluster.

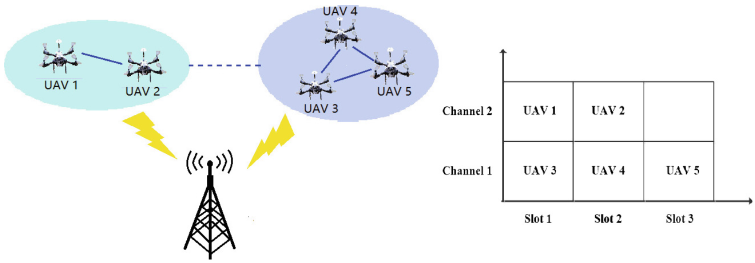

Fig. 1. Corresponding interference graph of the multi-UAV network example, where the dotted lines represent the interference between two UAV clusters while the solid lines mean the interference among the UAVs in the same cluster.

Denote UAV set and cluster set as $\mathcal{N} = \{1, 2, ..., N\}$ and $S_{\mathcal{Q}} = \{S_1, S_2, ..., S_Q\}$ respectively; moreover, the set of the available channel is $\mathcal{M} = \{1, 2, ..., M\}$. Similarly, the time slot set is denoted as $\mathcal{T} = \{1, 2, ..., T\}$. Suppose that the UAVs in the same cluster affect each other due to the connectivity inside the UAV cluster. Meanwhile, when the distance between two clusters is far enough, they will not cause mutual interference when choosing the same channel at the same time. That is, the communication of any cluster only directly affects the neighboring clusters. Therefore, for an arbitrary UAV n, the interference can be divided into intra-cluster and inter-cluster interference level. Motivated by these observations, we define the set of UAVs which are located in the same cluster with UAV n as $U_n = \{i \in S_q, i \neq n\}$. Similarly, we denote the neighboring UAV cluster set of UAV cluster S_q as J_{S_q}, i.e., $J_{S_q} = \{S_k \in S_{\mathcal{Q}} : d_{S_q S_k} < d_0\}$; moreover the set of UAVs in the J_{S_q} can be defined as $J_n = \{j \in S_k : S_k \in J_{S_q}\}$. An example topology of multi-UAV network is illustrated in Fig. 1.

2.2 Problem Formulation

Suppose that all channels and time slots are available for multi-UAV network. The interference emerges when two or more UAVs select the same channel to communicate at the same time. Let $a_n = (c_n, t_n)$ be the channel and slot chosen by UAV n, where $c_n \in \mathcal{M}, t_n \in \mathcal{T}$. The intra-cluster and inter-cluster interference level are defined as follows.

$$s_{n(in)} = \sum_{i \in \mathcal{U}_n} f(a_n, a_i) \tag{1}$$

$$s_{n(out)} = \sum_{i \in \mathcal{J}_n} f(a_n, a_i). \tag{2}$$

where $f(a_n, a_i)$ is the function defined as:

$$f(a_n, a_i) = \begin{cases} 1, & c_n = c_i \quad and \quad t_n = t_i \\ 0, & others. \end{cases} . \tag{3}$$

Note that $s_{n(in)}$ and $s_{n(out)}$ are in different positions, we consider the weighted interference level as $s_n = \alpha s_{n(in)} + (1-\alpha)s_{n(out)}$, where α is weight satisfies $0 < \alpha < 1$. Then we have:

$$s_n = \alpha \sum_{i \in U_n} f(a_n, a_i) + (1-\alpha) \sum_{i \in J_n} f(a_n, a_i). \tag{4}$$

The weight α is designed to balance the tradeoff between $s_{n(in)}$ and $s_{n(out)}$. Obviously, the influence of the intra-cluster interference is more serious than the other one. Therefore, we usually have $0.5 < \alpha < 1$.

The individual interference will be minimized if the number of UAVs using the same channel resource to communicate at the same time decreases. Therefore, in order to guarantee communication quality, we need to find an optimal combination of the joint channe-slot selections to minimize the aggregate interference level of all UAVs in the multi-UAV network, namely:

$$P1 : a \in \min \sum_{n \in \mathcal{N}} s_n. \tag{5}$$

3 Weighted Interference Minimization Game and Distributed Learning Algorithm

3.1 Weighted Interference Minimization Game Model

We formulate the problem of joint channel-slot selection for multi-UAV network mentioned above as a non-cooperative game, which is denoted as $\mathcal{F} = \{\mathcal{N}, \{\mathcal{A}_n\}_{n\in\mathcal{N}}, \{u_n\}_{n\in\mathcal{N}}\}$. In this game, $\mathcal{N} = \{1, 2, ..., N\}$ is a set of UAVs, which are regarded as the players in this game. $\mathcal{A}_n$ is a set of available actions for UAV n, and u_n is the utility function of UAV n. For presentation, the action space of UAV n is $\mathcal{A}_n = \{c_1, c_2, ..., c_M\} \otimes \{t_1, t_2, ..., t_T\}$, where "$\otimes$" is the Cartesian product. $u_n(a_n, a_{-n})$ is regarded as the utility function of the game, where $a_n = (c_n, t_n)$ is the action of UAV n, and $a_{-n} = (c_{-n}, t_{-n})$ represents the action profile of all UAVs excluding UAV n. Since the analysis of the interference mentioned before, the utility of any UAV n is influenced by its own action and the action profile of UAVs in U_n and J_n [8]. Therefore, we can define the set $B_n = U_n \cup J_n$, and then the utility function of UAV n can be expressed as $u_n(a_n, a_{B_n})$.

Note that in order to guarantee the communication connectivity and individual performance, each UAV expects to experience a lower interference level. Thus, we design the utility function as follows:

$$u_n(a_n, a_{B_n}) = -s_n. \tag{6}$$

where s_n represents the weighted interference level of UAV n which is specified by (4). Therefore, the ultimate goal of the proposed game is to maximize the utility function for each UAV, namely:

$$\max_{a_n \in \mathcal{A}_n} u_n(a_n, a_{B_n}), \forall n \in \mathcal{N}. \tag{7}$$

3.2 Analysis of Nash Equilibrium

Nash equilibrium (NE) [11] is the well-known stable solution in game model. Exact potential game (EPG) [11] is one of the most attractive potential games with several perfect features. For a game, it is an EPG if the change in the utility of an arbitrary player because of its own selection deviation leads to exactly the same in the potential function. The most important and excellent properties of EPG are: (1) every EPG has at least one pure-strategy NE, (2) the NE is the solution that can optimize the problem. We study the existence of NE for the weighted interference minimization game and the following theorem provides characterization of the formulated game.

Theorem 1. *The weighted interference minimization game $\mathcal{F}$ is an EPG with at least one pure-strategy NE. The solution can minimize the aggregate interference level of the multi-UAV network.*

Proof. Motivated by [8], we can obtain the following potential function:

$$\begin{aligned}\phi(a_n, a_{-n}) &= -\tfrac{1}{2}\sum_{n\in\mathcal{N}} s_n(a_1, a_2, ...a_N)\\ &= \underbrace{-\frac{1}{2}\alpha\sum_{n\in\mathcal{N}}\sum_{i\in U_n} f(a_n, a_i)}_{\phi1(a_n,a_{-n})}\underbrace{-\frac{1}{2}\beta\sum_{n\in\mathcal{N}}\sum_{i\in J_n} f(a_n, a_i)}_{\phi2(a_n,a_{-n})}.\end{aligned} \tag{8}$$

Then, we define $\mathcal{I}_n(a_n, a_{U_n})$ as the set of UAVs in U_n using the same channel to communicate at the same time slot with UAV n, i.e.

$$\mathcal{I}_n(a_n, a_{U_n}) = \{i \in U_n : a_i = a_n\} \tag{9}$$

where U_n is the set of UAVs located in the same cluster with UAV n. Then the notation $|\mathcal{I}_n(a_n, a_{U_n})|$ means the number of UAVs in $\mathcal{I}_n(a_n, a_{U_n})$. Similarly, $\mathcal{H}_n(a_n, a_{J_n})$ can be defined as follows:

$$\mathcal{H}_n(a_n, a_{J_n}) = \{i \in J_n : a_i = a_n\}. \tag{10}$$

Accordingly, the utility function can be given as follows:

$$u_n(a_n, a_{B_n}) = \underbrace{-\alpha\,|\mathcal{I}_n(a_n, a_{U_n})|}_{u1_n(a_n,a_{B_n})}\underbrace{-\beta\,|\mathcal{H}_n(a_n, a_{J_n})|}_{u2_n(a_n,a_{B_n})}. \tag{11}$$

Note that the mathematical forms of the intra-cluster and inter-cluster interference are similar, for the sake of simplicity, we only give the proof of intra-cluster interference.

It is assumed that an arbitrary UAV n in the network changes its joint channel-slot selection from $a_n = (c_n, t_n)$ to $a_n^* = (c_n^*, t_n^*)$ while others keep their selections unchanged. The change in utility function $u1_n(a_n, a_{B_n})$ is $\varDelta u1_n$:

$$\varDelta u1_n = u_n(a_n^*, a_{B_n}) - u1_n(a_n, a_{B_n}) = \alpha[|\mathcal{I}_n(a_n, a_{U_n})| - |\mathcal{I}_n(a_n^*, a_{U_n})|]. \tag{12}$$

Then we discuss the change in $\phi 1(a_n, a_{-n})$ due to the unilateral joint channel-slot selection change of UAV n is $\Delta\phi 1$:

$$\begin{aligned}\Delta\phi 1 = \tfrac{1}{2}\alpha\{\, |\mathcal{I}_n(a_n, a_{U_n})| - |\mathcal{I}_n(a_n^*, a_{U_n})| + \sum_{k\in\mathcal{I}_n(a_n, a_{U_n})} [|\mathcal{I}_k(a_k, a_{U_k})| - \left|\mathcal{I}_k(a_k, a_{U_k}^*)\right|] \\ + \sum_{k\in\mathcal{I}_n(a_n^*, a_{U_n})} [|\mathcal{I}_k(a_k, a_{U_k})| - \left|\mathcal{I}_k(a_k, a_{U_k}^*)\right|] + \sum_{k\in\mathcal{I}, k\neq n} [|\mathcal{I}_k(a_k, a_{U_k})| - |\mathcal{I}_k(a_k^*, a_{U_k})|]\}\end{aligned} \tag{13}$$

In (13), we define $\mathcal{I} = \mathcal{N}\backslash\{\mathcal{I}_n(a_n, a_{U_n}) \cup \mathcal{I}_n(a_n^*, a_{U_n})\}$. It means that $\mathcal{I}_n(a_n, a_{U_n})$ and $\mathcal{I}_n(a_n^*, a_{U_n})$ are excluded from $\mathcal{N}$. Since the selection of UAV n only affects the UAVs in U_n, the following equations hold:

$$|\mathcal{I}_k(a_k, a_{U_k})| - \left|\mathcal{I}_k(a_k, a_{U_k}^*)\right| = 1, \forall k \in \mathcal{I}_n(a_n, a_{U_n}) \tag{14}$$

$$|\mathcal{I}_k(a_k, a_{U_k})| - \left|\mathcal{I}_k(a_k, a_{U_k}^*)\right| = 1, \forall k \in \mathcal{I}_n(a_n^*, a_{U_n}) \tag{15}$$

$$|\mathcal{I}_k(a_k, a_{U_k})| - |\mathcal{I}_k(a_k^*, a_{U_k})| = 0, \quad \forall k \in \mathcal{I}, k \neq n. \tag{16}$$

The detailed proof of inter-cluster interference is omitted here to avoid unnecessary repetition. According to the equations above, we can easily have:

$$u_n(a_n^*, a_{B_n}) - u_n(a_n, a_{B_n}) = \phi(a_n^*, a_{-n}) - \phi(a_n, a_{-n}). \tag{17}$$

The Eq. (17) satisfies the definition of EPG [12]. Due to the attractive features of EPG, Theorem 1 is proved. □

3.3 Distributed Stochastic Learning Automata Based Algorithm

The distributed algorithm without information exchange is needed with the aim of achieving the NE more practically. We use a distributed SLA based algorithm which is proposed in [7]. In this algorithm, each UAV selects its channel and time slot in accordance with its mixed strategy, and then updates its mixed strategy according to certain rules in (18) which is related to the received random payoff. The algorithm in detail is given later and the asymptotic behavior of the algorithm is given and proved in [7] (Theorem 6).

The received payoff function can affect the selections of UAVs and influence the performance of the learning algorithm. In order to develop comprehensive random payoff and make full use of the unique feature of the multi-UAV network, we consider the received random payoff from two aspects. On the one hand, each UAV wants to mitigate the experienced interference, which motivates us to develop the random payoff as the decreasing function of the interference level. On the other hand, when an arbitrary UAV chooses the same channel with the UAVs in the same cluster at different time slots, it can get reward value.

According to the analysis above, we design the following random payoff received by UAV n:

$$r_n(k) = D - \varepsilon \cdot s_n + \eta \sum_{i\in U_n} g(a_n, a_i). \tag{20}$$

Algorithm 1. The Distributed SLA Based Joint Channel and Time Slot Selection Algorithm

Initialization: set $k = 1$ and initialize each UAV's joint channel and time slot selection probability vector to $q_{nm}(k) = \frac{1}{MT}, \forall n \in \mathcal{N}, m \in \mathcal{A}_n$.
Loop $k = 1, 2, ...$
1: Each UAV n randomly selects its action $a_n(k) = (c_n(k), t_n(k))$ in accordance with its current selection probability vector $\mathbf{q}_n(k)$.
2: Each UAV uses selected actions to communicate and then receives a random payoff $r_n(k)$ characterized by (22).
3: According to the received random payoff, each UAV follows the following rules to update their probability vector:

$$\begin{array}{ll} q_{nm}(k+1) = q_{nm}(k) + \sigma\tilde{r}_n(k)(1 - q_{nm}(k)), & m = a_n(k) \\ q_{nm}(k+1) = q_{nm}(k) - \sigma\tilde{r}_n(k)q_{nm}(k), & m \neq a_n(k) \end{array}. \tag{18}$$

where σ is the learning step size satisfies $0 < \sigma < 1$ and $\tilde{r}_n(k)$ is the following normalized received payoff:

$$\tilde{r}_n(k) = r_n(k)/r_{\max}. \tag{19}$$

where $r_{\max} = D + \eta \cdot (T - 1)$ is the interference-free and reward-full payoff, T is the number of time slots.
End Loop

where $D > 0$ is a predefined constant so that the received payoff remains positive, ε and η are weights, s_n is the weighted interference level and $g(\cdot)$ is the function defined as follows:

$$g(a_n, a_i) = \begin{cases} 1, & c_n = c_i \quad and \quad t_n \neq t_i \\ 0, & others. \end{cases}. \tag{21}$$

In (20), the purpose of the proposed weights ε and η are to balance the experienced interference and received reward. The function $g(\cdot)$ means the number of UAVs in the same cluster with UAV n which choose the same channel but the different time slots compared with UAV n. However, the predefined positive constant D affects the convergence of the algorithm if D is too large. On the contrary, if D is too small, the received random payoff will be negative. Thus we modify:

$$r_n(k) = \max\{r_n(k), 0\}. \tag{22}$$

4 Simulation Results and Discussion

We conduct the simulation from three aspects: the influence of weight α, convergence behavior and performance evaluation so as to demonstrate the effectiveness of the SLA based algorithm and the formulated game model. All UAVs located in a 1000 m $\times$ 500 m rectangle region. To distinguish the neighboring UAV clusters, we set the distance as 150 m. There are $M = 2$ channels and $T = 2$ time slots. In order to reduce the interference among UAVs and increase the probability for UAVs located in the same cluster to choose the same channels, we choose $\varepsilon = 0.7$ and $\eta = 0.3$. The learning step size is $\sigma = 0.15$ and the predefined constant $D = 1.8$.

4.1 The Influence of Weight α

The weight α is designed to measure the importance of intra-cluster interference. A larger value for the weight α will increase the significance of intra-cluster interference. Figure 2 shows the variation trend of the two kinds of interference when α ranges from 0 to 1. There is an upward trend in the inter-cluster interference when α increases from 0 to 1. That means smaller α leads to lower inter-cluster interference level. When $\alpha = 0$, that means we only consider the inter-cluster interference no matter how high the intra-cluster interference is and vice versa. We choose $\alpha = 0.7$ in this simulation.

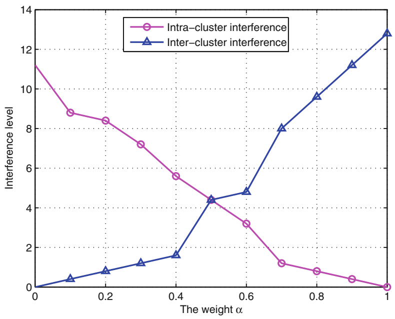

Fig. 2. The interference level comparison with different weight α.

4.2 Convergence Behavior

Figure 3 illustrates a considered multi-UAV network topology where the neighboring UAV cluster sets vary from cluster to cluster. For example, the neighboring UAV cluster set of the 4 clusters are $J_{S_1} = \{2\}$, $J_{S_2} = \{1, 3, 4\}$, $J_{S_3} = \{2, 4\}$ and $J_{S_4} = \{2, 3\}$ respectively.

The joint channel and slot selection probabilities of UAV cluster S_1 is presented in Fig. 4. At the beginning, UAV 1 and UAV 2 choose actions randomly with equal probabilities. As the algorithm iterates, they finally converge to different selections. Moreover, Table 1 shows the selections of all UAVs. We can summarize that each UAV select the same channel but different slots due to the reward when there are only two UAVs in the same cluster. When the number of UAV becomes larger, other UAVs select the other channel because the intra-cluster interference is more serious. The results validate the effectiveness of the payoff function.

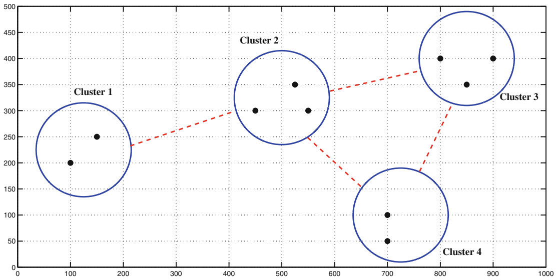

Fig. 3. An example topology of the multi-UAV network with 10 UAVs and 4 clusters lcoated in the rectangle region. The small solid black dots represent the UAVs and the large dashed blue circles mean the UAV clusters. The red dotted lines represent the existence of interference between the two clusters. (Color figure online)

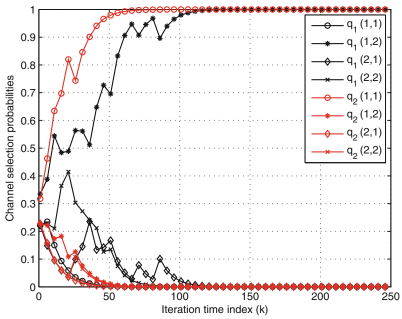

Fig. 4. The convergence of the SLA based algorithm of UAV cluster S_1

Table 1. Joint channel and slot selections of UAVs

UAV cluster	UAV	Channel selection	Slot selection
S_1	No. 1	1	2
	No. 2	1	1
S_2	No. 3	2	1
	No. 4	1	1
	No. 5	2	2
S_3	No. 6	2	1
	No. 7	1	1
	No. 8	1	2
S_4	No. 9	2	2
	No. 10	2	1

4.3 Performance Evaluation

First, we compare the aggregate interference level in different scenarios. We consider the multi-UAV network involving 2 channels, 2 slots and the number of UAVs increasing from 8 to 14 located in each cluster randomly. For comparison, we develop 4 methods: random selection, best NE, worst NE, and the SLA based algorithm. The results shown in Fig. 5 can be listed as follows: (i) when the number of the UAVs becomes larger, the aggregate interference level becomes higher; (ii) the learning solution is almost the same as the best NE because the learning solution asymptotically achieves global optimum.

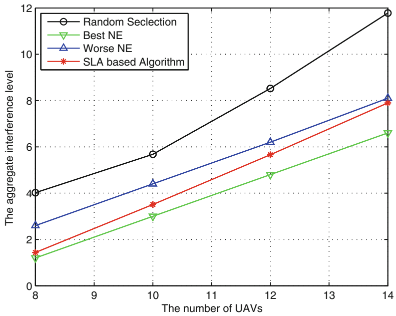

Fig. 5. The aggregate interference level when varying the number of UAVs. The number of channels and slots are $M = 2$ and $T = 2$ respectively.

Second, we compare the aggregate interference level in different numbers of available channels. We consider 5 approaches: optimal, random selection, best NE, worst NE, and the SLA based algorithm. Figure 6 shows the comparison among the 5 methods in terms of the aggregate interference level by increasing the channels from 1 to 4. Some significant results can be obtained from the

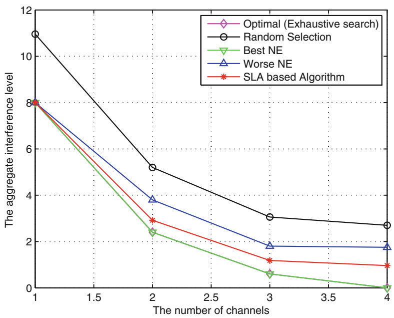

Fig. 6. The aggregate interference level when varying the number of channels. The simulation scenario is given in Fig. 3. The number of slots is $T = 2$.

Fig. 6: (i) with the increase of the number of channels, the aggregate interference level becomes lower; (ii) the best NE can obtain the best performance which is the same as the optimal one (exhaustive search), and the learning solution is very close to them; (iii) when the number of channel is 4, it means there are 8 selections for each UAV, the system can fulfill the demand of the UAVs.

5 Conclusion

In this article, we investigated the problem of distributed opportunistic spectrum access under the consideration of channel-slot selection simultaneously in multi-UAV network from a game-theoretic perspective, and took into account the distinctive features of the multi-UAV network. We formulated the joint channel-slot selection problem as a weighted interference minimization game. We proved that the weighted interference minimization game is an exact potential game with, and then used the distributed stochastic learning automata based joint channel and time slot selection algorithm to achieve the Nash equilibrium. The algorithm did not need information exchange among UAVs in the network which was more suitable for dynamic and practical enviroment. The simulation results showed that the learning solution was almost the same as the optimal solution which validated the effectiveness of the algorithm.

There are still several potential research issues needed to be studied. For instance, the ground station can allocate different numbers of time slots to different UAV clusters dynamically due to its load. Moreover, we can consider the business requirements for different UAVs and the formation of the UAV clusters. The resaerch of these factors will continue in the future.

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