Autonomous Deployment of UAVs as Access Points to Serve Wireless Terminals

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***Abstract*—Unmanned aerial vehicle (UAV) nowadays are inexpensive and can serve as a robust communication platform in the sky. Using UAV as access point can be particularly helpful for wireless terminals in areas where terrestrial infrastructure is absent or damaged. The problem is how to deploy a fleet of UAVs to efficiently cover scattered terminals while not wasting too much energy on the deployment process. In this paper, we propose two autonomous service deployment approaches for UAVs based on game theory. In these approaches, UAVs adaptively adjust their locations based on local information rather than instructions from a control station. Experimental results show that the proposed approaches outperform existing approach in terms of average spectral efficiency and UAV travelling distance.**

I. Introduction

Due to high mobility and affordable price, unmanned aerial vehicle (UAV) has found many civilian applications in the past decade. These applications include surveillance and monitoring tasks (e.g., traffic monitoring), search-and-rescue, remote sensing or data collection from remote sensors [1], and deployment of a micro cloud infrastructure in the sky [2]. UAVs can also be used to extend communication capability by relaying wireless signal, disseminating or collecting information, and providing wireless coverage within a serving area [3].

Wei et al. [4] analyzed the capacity and delay of UAV networks, where a number of UAVs are used to monitor three-dimensional environment. Fadlullah et al. [5] considered a swarm of UAVs which are remotely controlled by a control station to form a multi-hop network. They proposed a scheme to enhance the probability of link connections and coverage area by dynamically adjusting the distance between the centers of trajectories of two neighboring UAVs.

This paper considers using UAV as access point to provide wireless access service to terminals on the ground. This is particularly useful in dangerous or inaccessible areas, or when network infrastructure is temporarily not functional or damaged due to attack or natural disaster. We study how to efficiently and effectively deploy a fleet of UAVs serving as access points in an area of interest.

A control station that has the visibility over all terminals may calculate the optimal deployment of UAVs and then dispatch each UAV to a designated serving spot. However, such a scheme may not be feasible or scalable. Therefore, we consider an autonomous approach for UAV deployment, where each UAV independently finds and moves to a location to serve ground terminals without human intervention or external instructions. The objective is two-fold: to minimize energy consumption of UAVs and to maximize downlink (from UAV to terminal) spectral efficiency. Energy consumption of a UAV includes energy spent on communication and maneuver. Spectral efficiency depends on aggregated signal-to-interference ratios (SIRs) experienced by served terminals. Since we are primarily concerned with path loss when gauging SIRs, the efficiency heavily depends on relative distance between UAV and terminal.

Our work is most closely related to Gruber's [6], which also proposed an autonomous navigation scheme for UAV serving as access points. Both approaches demand no coordination among UAVs and thus save energy on inter-UAV communication. A UAV in Gruber's scheme attempts moving toward some location where the average SIR experienced by all terminals associated with it is maximized. However, as UAV cannot know the resulting SIR value at the next spot before it actually moves to that spot, UAV in fact decides its next move based on the spectral efficiency gain of its previous move. It maintains its current direction if there is a efficiency gain and changes to a arbitrary direction otherwise.

Gruber's work has two limitations. First, it does not consider energy consumption on navigation. As a result, UAV may circle around a small region without any significant improvement on spectral efficiency. Second, his work assumed that every terminal is able to detect signal from any UAV in the deployment field when gauging its SIR value. This is not possible in practice when the terminal is very far away from UAV. In that case, a UAV may detect no efficiency gain and thus waste time and energy on wandering around a region.

The proposed approach overcomes the above-mentioned limitations by two techniques. First, a UAV stops moving when it realizes that no performance improvement can be gained by further move. Second, when a UAV detects no signal from any terminal, it randomly selects a target destination to move toward. If it detects any terminal during the movement, it starts moving toward the terminal and attempts to increase spectral efficiency. We formulate a generic game to model the behaviors of UAVs, and derive two practical schemes from the generic game model. One scheme attempts reducing the distance from UAV to some associated terminal without increasing those to others. The other scheme attempts minimizing the average distance from UAV to all terminals associated with it. Simulation results show that both schemes outperform Gruber's approach in terms of UAV travelling distance. Concerning spectral efficiency, one of the derived scheme performs the best.

The rest of this paper is organized as follows: Sec. II reviews related literature. Sec. III presents the proposed game-theoretic approaches to UAV deployment problem. Sec. IV presents experimental results. The last section concludes this work.

II. Related work and Background

The idea of using UAV as access point is not new. Koulali et al. [7] proposed an autonomous beacon scheduling scheme for UAVs to avoid possible overlapping beacon intervals with neighboring UAVs. Lyu et al. [8] proposed a centralized UAV dispatch algorithm that attempts to serve a collection of terminals with known locations using a minimal number of UAVs. Gruber [6] proposed a decentralized UAV placement algorithm inspired by bacterial chemotaxis for a fixed number of UAVs to serve terminals with unknown locations. The goal of the deployment is to maximize average downlink spectral efficiency.

Assume that we have n UAVs numbered from 1 to n. For a terminal t that is associated with UAV i, the SIR from i to t is defined as

$$SIR_{i,t} = \frac{R_{i,t}}{\sum_{j \neq i} R_{j,t}}, \tag{1}$$

where $R_{k,t}$ is the received signal strength (RSS) of signal from UAV k measured at t. As [6], we ignore shadowing and fading effects. Therefore, the value of $R_{k,t}$ is the transmission power of UAV k subtracted by the path loss from the UAV to the terminal.

Let d and θ be the distance and elevation angle, respectively, between a UAV u and a terminal t. Gruber [6] used (2) to calculate the mean path loss (in dBm) from the UAV to the terminal, taking into consideration of both d and θ.

$$\mathrm{PL} = \begin{cases} 98.4 + \log(d) + \frac{2.55+\theta}{0.0594+0.04066\theta}, & \text{if } 0^\circ \leq \theta < 10^\circ, \\ 98.4 + \log(d) + \frac{-94.2+\theta}{-3.44+0.0318\theta}, & \text{if } 10^\circ \leq \theta \leq 90^\circ. \end{cases} \tag{2}$$

We assume that each terminal is associated to the UAV with the highest SIR value (as in [6]) and reports its SIR to the UAV via a reverse link. Let Ω_i be the set of terminals that are currently associated with UAV i. The average downlink spectral efficiency of UAV i is [6]

$$SE_i = \frac{\sum_{t \in \Omega_i} \log_2(1 + SIR_{i,t})}{|\Omega_i|}. \tag{3}$$

The performance of UAV deployment algorithm is measured by the average spectral efficiency as defined in [6].

$$\Lambda = \frac{\sum_{i=1}^{n} SE_i \cdot |\Omega_i|}{m}, \tag{4}$$

where m is the total number of terminals in the deployment field.

One limitation of Gruber's work is that it did not consider minimum detectable signal (MDS). In practice, a receiver can only detect signal significantly stronger than background noise. Since in Gruber's scheme, a UAV has to make random movements when no terminal is associated to it, UAVs may make a lot of random movements concerning the effect of MDS. In other words, the performance of Gruber's scheme may degrade when the effect of MDS is taken into account.

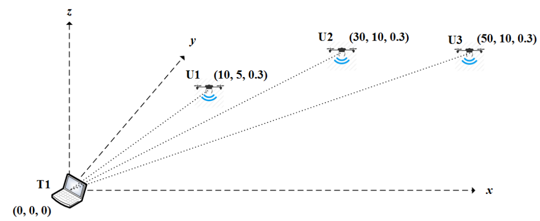


Fig. 1. A scenario with one terminal and three UAVs

For example, consider the scenario shown in Figure 1, where there are three UAVs (U1, U2 and U3) and one terminal (T1). Suppose that the transmission power of each UAV is fixed to 46 dBm and the minimal detectable signal strength is -100 dBm. By (2), $R_{1,1}$, $R_{2,1}$, and $R_{3,1}$ will be -106.9, -120.4 and -126.1 (all in dBm), respectively. In Gruber's work, T1 will be associated with U1 with $SIR_{1,1} = 17.6$. However, because all the RSS values are below -100 dBm, T1 in practice probably detects no signal at all and thus is associated to no UAV.[1] Consequently, all UAVs in Figure 1 must make random movements. In contrast, Gruber's work assumes that U1 can maintain its moving direction.

III. The Proposed Approach

A. Problem Definition and the Game Model

UAVs are mobile while terminals are assumed stationary or quasi-stationary. A terminal is associated to no UAV if it detects no UAV with SIR value equal to or above 0.1. If there is at least one UAV with SIR value equal to or above 0.1, the terminal selects a UAV with the highest SIR value. The above-mentioned setting was originally stated in Gruber [6].

To decide whether to keep the current moving direction, a UAV in [6] must have the knowledge of the SIR values of all the terminals associated with it. In contrast, the proposed approach does not demand that knowledge from UAVs. Only after the deployment is the spectral efficiency measured. We do, however, require that each UAV know the distance from it to every terminal associated with it. We assume that the distance is calculated based on the location of the terminal. We assume that terminals inform the UAV they choose to associate via a uplink channel. During or after association, terminals then pass their geographic location information (.i.e., coordinates) to the UAV through uplink channel.

We assume m terminals and n UAVs deployed in an $r \times r$ area. Let $T = \{t_1, t_2, \ldots, t_m\}$ be the set of terminals, $P = \{p_1, p_2, \ldots, p_n\}$ be the set of all UAVs, and $L = \{l_1, l_2, \ldots, l_n\}$ be the set of locations corresponding to P, where $l_i = (i.x, i.y, i.z)$ represents p_i's coordinate in three-dimensional space. We define UAV terminal coverage game as follows. P is the set of players. The strategy set for

[1] In this case, T1 detects no signal from a UAV once its distance to the UAV is larger than 15 km.

player represents the set of possible next locations. Given that the current location of player p_i is l_i, the strategy set for p_i is $S_i = \{s_i | s_i = l_i + o_i, o_i \in O\}$, where $O = \{(a, 0, 0), (-a, 0, 0), (0, a, 0), (0, -a, 0), (0, 0, 0)\}$ is the set of feasible movements (a is a constant). Note that UAVs do not change their altitude because Gruber [6] reported that UAV has best spectral efficiency with altitude fixed at 300 m.

A strategy profile $C = \{s_1, s_2, \ldots, s_n\}$, where $s_i \in S_i$, is a tuple of strategies, one from each player. For each p_i, $1 \le i \le n$, $u_i(C)$ is the utility function defined for p_i that determines the payoff of p_i with respect to a specific strategy profile C. The goal of UAV placement game $G = [P; \{S_i\}_{i=1}^n; \{u_i\}_{i=1}^n]$ is to maximize the utility function of each player. To motivate each player to increase the number of associated terminals and also spectral efficiency, a possible definition of $u_i(C)$ is

$$u_i(C) = |\Omega_i| \times \mathit{SE}_i. \quad (5)$$

In this way, Λ is proportional to the social welfare (i.e., $\sum_i u_i(C)$) of the game.

A problem with (5) is that a player may be in a situation where $|\Omega_i| = 0$ for every strategy $s_i \in S_i$. In this case, the player is unable to benefit from altering its strategy and may have to make an inefficient movement like random walk. To deal with this situation, we use the notion of random waypoint (RWP) [9] to escape from the current spot l_i. The idea is to let the player randomly pick up a new destination.[2] The player then moves toward that destination with unit step size a. If the player finds some terminal association before reaching the destination, the player aborts the RWP process and makes subsequent moves based on its utility function. If the player does not have any terminal association before reaching the destination, it repeats the above RWP process until at least one terminal is located.

Another problem with (5) is that to evaluate the payoff of some strategy $s_i \in S_i$, p_i has to know the values of $|\Omega_i|$ and SE_i at the next spot s_i. However, the only way to get this information is through the feedback sent by terminals that are associated with p_i when p_i is at s_i. This means p_i needs future information to make a correct decision. In the following, we show two variants of the game which make decisions based on current information.

B. Pareto Improvement Approach (PIA)

In this approach, player p_i only cares about the distance from it to every terminal currently associated with it. More specifically, UAV only considers strategies that decrease its distance to some associated terminal without increasing the distance to any associated terminal. If more than one strategies are qualified, UAV choose the one that yields the most distance reduction. Formally, let $\mathit{dist}(s, t)$ be the distance from some spot s to the location of terminal t. Let $D = (d_1, d_2, \ldots, d_k)$ and $D' = (d'_1, d'_2, \ldots, d'_k)$ be two k-tuples and define $D \prec D'$ if $\forall i, 1 \le i \le k : d_i \le d'_i$ and $\exists j, 1 \le j \le k : d_j < d'_j$. Let

[2]When picking up the destination, the z-coordinate remains unchanged because altering z-coordinate does not help much in finding terminals compared with the change of x or y coordinate.

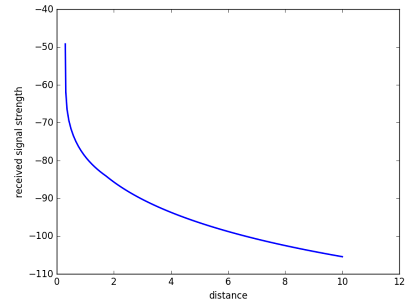


Fig. 2. RSS with respect to the transmitter-receiver distance

$\Omega_i(s)$ be the set of terminals associated with p_i when p_i is at some spot s. Assume that the current location of p_i is l_i and, without loss of generality, that $\Omega_i(l_i) = \{t_1, t_2, \ldots, t_k\}$. Let $D(s) = (\mathit{dist}(s, t_1), \mathit{dist}(s, t_2), \ldots, \mathit{dist}(s, t_k))$. In this approach, the strategy set of p_i is $S_i = \{s_i | s_i \in S_i, D(s_i) \prec D(l_i)\}$. If $|S_i| > 1$, p_i chooses $s_i \in S_i$ that maximizes $\sum_{1 \le j \le k}(\mathit{dist}(l_i, t_j) - \mathit{dist}(s_i, t_j))$.

If there is only one UAV in the system, the UAV will eventually reach the location where it cannot further reduce the distance to any associated terminal. During its movement, it may attract additional associations from other terminals. However, as terminals already associated cannot change or lose their associations and the number of terminals is finite, the stability of PIA is guaranteed.

Now consider the interactions among UAVs. It is possible that a terminal originally associated with UAV p_i changes its association to UAV p_j if the SIR with p_j is higher than that with p_i after p_i's and p_j's movements. It is a concern whether the dynamics of association change cause instability of the scheme.

To see the stability of PIA, consider first the case that p_i and p_j do not move at the same time. As illustrated in Figure 2, $R_{i,t}$ is strictly increasing as the distance between p_i and t decreases. Therefore, after p_i's movement, all terminals in Ω_i are still associated with p_i and get shorter distances to p_i.

Now consider the case when two UAVs p_i and p_j move at the same time (during which all other UAVs do not change their locations). For any terminal that is still associated with p_i after the movements, its distance to p_i decreases. For any terminal t that changes its association from p_i to p_j after the movements, Lemma 1 indicates that $R_{j,t} > R_{i,t}$ and thus $\mathit{dist}(s_j, t) < \mathit{dist}(s_i, t)$ after the movements. Suppose that p_i moves from l_i to s_i. Because $\mathit{dist}(s_i, t) \le \mathit{dist}(l_i, t)$, the distance of t to the associated UAV decreases after the movements (despite t's change of association).

Lemma 1: For any terminal t and any two UAVs p_i and p_j, $\mathit{SIR}_{i,t} > \mathit{SIR}_{j,t}$ if and only if $R_{i,t} > R_{j,t}$.

Proof: (skipped due to space limitation) ∎

Therefore, regardless whether terminals change their associations, any UAV's movement can only reduce a terminal's distance to the UAV it is associated with. Let us define *distance vector* to be an m-tuple that represents the distance from each terminal to its associated UAV.[3] PIA ensures that every move taken by a UAV always causes a Pareto improvement (i.e., a distance reduction on some terminal without any distance increase on any others) on the distance vector. This is the reason why PIA is named so.

However, the claim of Pareto improvement holds only if no associated terminal ever becomes unassociated (i.e., associated with no UAV) due to UAV's movements. Theoretically speaking, a terminal associated with some UAV may become unassociated due to increased interference from other UAVs. However, this can only occur to terminals on the boundary of the UAV's service coverage area. We treat this as a temporary disturbance in the way to stability.

C. *Minimize Average Distance to Terminals (MAD2T)*

Although PIA guarantees stability, its performance is not desirable. Thus, we propose another approach which minimizes the average distance to served terminals. Given that UAV p_i is at some spot s, let $avgd_i(s)$ be the average distance between s and the location of each terminal associated with p_i. Formally, assuming that the current location of p_i is l_i,

$$avgd_i(s) = \frac{\sum_{t \in \Omega_i(l_i)} dist(s,t)}{|\Omega_i(l_i)| + 1}. \quad (6)$$

Note that p_i is unable to predict the actual set of terminals that will make associations with it when it comes to s_i. That is the reason why we use $\Omega_i(l_i)$ instead of $\Omega_i(s_i)$ in the definition of $avgd_i(s)$.

In this approach, the strategy set of p_i is $S_i = \{s_i | s_i \in S_i, avgd_i(s_i) < avgd_i(l_i)\}$. If $|S_i| > 1$, p_i chooses $s_i \in S_i$ that maximizes $avgd_i(l_i) - avgd_i(s_i)$.

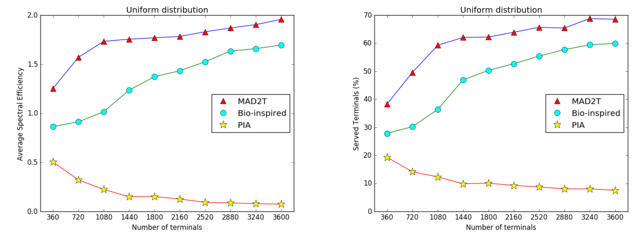
Note that every feasible move in PIA is also a feasible move in MAD2T, but the converse does not hold generally. The reason is that p_i using MAD2T may reduce the distance to some terminal at the cost of increasing some other's (as long as the average distance is decreased). This is not allowed in PIA.

IV. Simulation Results

We studied the performance of our approach and the work in [6] (called Bio-inspired hereinafter) by simulations. We used 20 UAVs with initial locations set to the same as that of [6]. We considered two different terminal distributions, namely, uniform distribution and clustered distribution, and varied the area size and the number of terminals. The result of each configuration was averaged over 50 trials. Each trail consists of 10,000 iterations (as in [6]) and every UAV makes a single move in each iteration. The order in which UAVs move was random. The moving distance (step size) for UAV in one iteration was 0.1 km.

We measured two metrics: average spectral efficiency and total traveling distance. The former measures the coverage quality of UAVs while the latter measures the cost.

[3] A terminal associated with no UAV has a distance of ∞.



(a) (b)

Fig. 3. (a) Average spectral efficiency versus the number of total terminals. (b) Percentage of served terminals versus the number of total terminals.

A. *Results With Uniform Distribution*

We first randomly placed 360 to 3600 terminals in a 60×60 km^2 deployment area by uniform distribution. Note varying the number of terminals effectively changes the density of terminals.

Figure 3(a) shows how the average spectral efficiency changes with the number of terminals. Because UAV's service coverage is fixed, the expected number of terminals within the coverage area increases with the terminal density. This explains the trend of increasing average spectral efficiency for Bio-inspired and MAD2T. However, UAV using PIA does not ever attempt increasing the distance to an associated terminal to increase spectral efficiency or potentially attract more terminal associations. For this reason, UAV using PIA may get trapped in a spot when the first time a terminal is associated with it. Consequently, UAV does not serve more terminals and thus we got lower average spectral efficiency with more terminals. Fig. 3(b) showing the percentage of served terminals confirms this effect.

MAD2T minimizes the average distance to all associated terminals. This implies that UAV using it tends to move toward the direction where the number of terminals is comparatively high. This explains why MAD2T performs better than Bio-inspired. The performance gap between MAD2T and Bio-inspired decreases when the number of terminals increases. The reason is that the percentage of served terminals starts to saturate after sufficiently many terminals are placed. This explains why the growth rates of average spectral efficiency in both approaches become smooth.

Concerning UAV travelling distance, PIA performed the best while Bio-inspired performed the worst. The reason is that UAVs using Bio-inspired make a move in every iteration even if no further improvement can be made. The travelling distance with MAD2T slightly increased with increased number of terminals. The reason is that increasing the number of terminals also increases the number of terminals receiving signals from UAVs when UAVs update their locations. Therefore, it takes a longer time for UAVs to stabilize.

B. *Results With Clustered Distribution*

We used clustered terminal distribution to test the robustness of deployment schemes when there may be no terminals close enough to guide the movements of UAVs. We placed 360

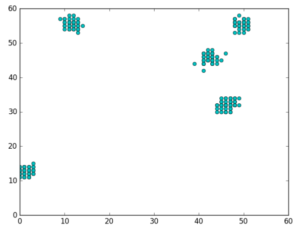
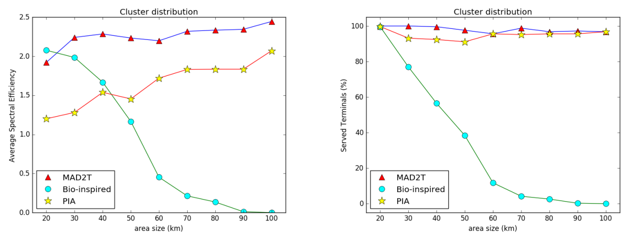


Fig. 4. Terminal distribution pattern in 60×60 km^2 deployment area



(a) (b)

Fig. 5. (a) Average spectral efficiency versus area size. (b) Percentage of served terminals versus the area size.

terminals based on the distribution pattern shown in Fig. 4. We varied the size of the deployment area and scaled up the coordinates of terminals and UAVs to be proportional to the area size.

Figure 5(a) shows the average spectral efficiency with respect to the area size. Bio-inspired performed well in 20×20 km^2 deployment area because therein 20 UAVs could effectively cover the entire deployment area. For that reason, spectral efficiency gain could always be measured and used to guild the movements of UAVs. As a result, Bio-inspired outperformed MAD2T. When the area size increases, UAVs using Bio-inspired might not successfully find nearby terminals to guide their movements. This can be confirmed with Fig. 5(b). Even though UAVs using PIA served more terminals than those using Bio-inspired, many terminals in the former case might not have good signal quality, as shown in Fig. 6. This justifies the result that the average spectral efficiency with PIA was worse than that with Bio-inspired when the area was not larger than 40×40 km^2.

Concerning travelling distance, Bio-inspired still performed

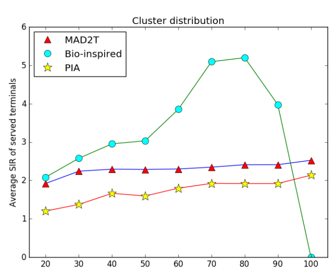
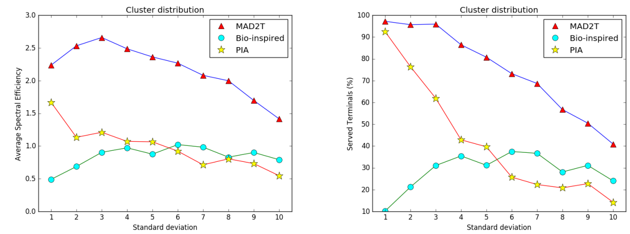


Fig. 6. Average SIR of served terminals with respect to the area size



(a) (b)

Fig. 7. (a) Average spectral efficiency versus the degree of clustering. (b) Percentage of served terminals versus the degree of clustering.

the worst. PIA and MAD2T performed nearly the same. Both incurred worse result with increased area size.

We also used two-dimensional Gaussian distribution with five given centers as shown in Fig. 4 to generate terminal locations. We adjusted the standard deviation of the distribution to control the degree of clustering and observed how the performance was affected. Fig. 7 shows how the average spectral efficiency and the percentage of associated terminals change with the standard deviation when 360 terminals was placed in a 60×60 km^2 area.

V. Conclusions

We have proposed two approaches to autonomous UAV deployment. One approach, PIA, seeks for Pareto improvements on the distance from UAV to each associated terminal. The other approach, MAD2T, attempts to minimize the average distance from UAV to all terminals associated with it. We have conducted simulations using both uniform and cluster terminal distributions to evaluate the performance of the proposed approaches. The result indicates that, in both distributions, MAD2T performed the best in terms of average spectral efficiency while PIA performed the best in terms of travelling distance.

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