A heap strategy for UAV deployment issues under mobile terrestrial wireless communication networks

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Abstract. Unmanned on-board mobile base stations (MBSs) can more effectively solve wireless connectivity problems in terrestrial communication networks without fixed infrastructure. The purpose of this article is to minimize the number of MBS required to provide wireless coverage for a set of distributed ground terminals (GTs). Traditional clustering algorithms are no longer applicable because each drone has a different coverage area size and the traditional K-Means clustering algorithm has no limit on the number of heaps that can exceed the maximum coverage area of a single drone, making it impossible for a drone to provide services. In response to this problem, the traditional K-Means clustering algorithm is optimized, and the results of the optimized K-Means clustering algorithm are stacked to ensure that each pile has the corresponding drone capability to serve it.

Keywords: Optimize the K-Means clustering algorithm ; Unmanned aerial vehicle

1. Introduction

1.1. background
Unmanned aerial vehicles (UAVs) have the advantages of low cost, zero risk of casualties, good mobility, etc., and are widely used in reconnaissance, combat, forest fire detection, communications, emergency search and rescue scenarios. In particular, mobile base stations (MBS) provide flexible, fast wireless connectivity. For example, when an earthquake or power failure occurs in a location and the ground base station is not working properly, the MBS installed by the drone can be deployed quickly to continue to provide wireless communication services to the ground terminal. Moreover, MBSs mounted on drones are often much higher than ground base stations, reducing interference from mountains or buildings. However, due to transmission power limitations, the MBS installed by the drone can only cover a limited number of GT. Therefore, when a large amount of emergency communication coverage is required, multiple interceptor systems installed by multiple drones should be deployed simultaneously. However, drones are more expensive to install MBSs than ground base stations, where infrastructure, such as fiber optics, antenna towers and engine rooms, can be expensive to purchase and install, especially in battlefields or natural disasters. Therefore, in order to reduce management and maintenance costs, the location of the drone mount missile should be optimized based on the known location of all GT to minimize the number of MBS.
Each drone flies at an irregular altitude $H$, while the drone-GT channel is dominated by the LOS link, and the quality of its channel depends largely on the drone-GT distance. We consider that no ground BS is available, that the MBS installed by the drone is connected via a satellite link loop, and that each MBS projection has a different coverage radius of $r$ on the ground, as shown in Figure 1, due to the drone's maximum coverage capability.

![Figure 1. UAV human matching diagram](image)

1.2. Description of the problem

In a two-dimensional plane, it is now necessary to have $m$ users gather around hot spots (e.g., shopping malls, residential areas), the location of any ground user is known in advance, and the ground base station is not available. Now you need to deploy an over-the-air wireless node to serve this $m$ user. There are known to be the following specifications of the aerial node set $N$, each air node has two antennas, one to serve ground users, one to interact with other air nodes information.

1. The number of users who are the largest service for an air node at the same time is $C_i$.
2. The air wireless node must be able to form a network (the signal quality of the air node is greater than one threshold $SNRa$, and each air node must be able to communicate in both directions with another air node).
3. Each user can only be serviced by one air node
4. Each user being serviced meets the service requirements (i.e., the signal-to-noise ratio to the drone providing the service is greater than one threshold $SNRg$).
5. There can be some users who are not serviced, but the ratio of the number of users to the total number of users serviced is greater than a threshold of $\tau$.

It is now necessary to find a minimum number of air nodes that meet the current regional service requirements under limited conditions and to optimize the 3D position of each air node to maximize the quality of service. Research and think about how to solve this problem.

1.3. Our work

1.3.1. Our steps for resolving are as follows. (1) First, mathematical knowledge is used to find out the optimal state of the drone under the four constraints. Get the height and maximum area that can be covered by each drone at optimal condition.

(2) Descend the drones in descending order of the maximum area that can be covered.

(3) The crowd is divided using the K-Means algorithm. (Optimization section: When stacking, the number of people per heap is controlled.) Make the number of people in the $i$th heap less than or equal to the maximum coverable area of the $i$th drone. For example: if the maximum coverage area of a drone
is sorted to 50,39,20,15, then the area of the first heap must be less than or equal to 50, and the second heap is less than or equal to 39... and so on.

(4) Match the man-heap to the drone in turn, and stop allocating the drone when the ratio of the number of services to the total number of people exceeds the specified threshold.

(5) In turn, the number of people changed, the number of drones, the distribution of the personnel matrix of these three variables, many experiments on the algorithm has been tested in different aspects.

1.3.2. Innovation point. In the third step of the heap, we optimized the k-means algorithm. Traditional K-Means algorithms divide different clusters by randomly generating k center points, calculating the distance from each center point to the k-center points, and re-clustering by calculating the center points of each cluster. However, since there is no limit to the size of the heaps that are eventually formed by this algorithm, it may eventually exceed the maximum coverage area of a single drone, making the drone unable to provide services. Therefore, based on this algorithm, this paper proposes an optimized MBS placement algorithm, that is, according to the coverage capability of the drone, the distributed ground terminal (GTs) are clustered and stacked, descending and placing MBS in turn. In the proposed optimization algorithm, we assume in advance that the flight altitude and maximum coverage area of each drone can be different, and require: "Air wireless nodes must be able to form a network (the signal quality of the air nodes is greater than one threshold, and each air node must be able to communicate in both directions with another air node); Can only be serviced by one air node; each user serviced to meet service requirements (i.e., the signal-to-noise ratio with the drone providing the service is greater than one threshold), and there may be some users who are not serviced, but whose ratio of the number of users to the total number of users is greater than one threshold τ. Numerical results show that the algorithm provides near-optimal performance for the number of mbss required. In addition, the algorithm requires better MBS and average time complexity than other scenarios.

2. System model

In order to keep the number of heaps as small as possible, we start with K-1. To determine whether the current heap result meets the conditions we set, and if so, the current heap result is the best result we can find:

```c++
int fenDui (int t, int kk) {
    K=kk;
    FenDui (t, K);
    //cout<<"indef=":<<indexFen<<endl;
    if (judge (t, numer, fly2Index, indexFen, x0)) {
        shuzu (t);
        fenDui (t, kk-x0+1);
    }
    else return fly2Index;
}
K=fenDui (t,1);
```

Let's take a look at our judgment. The divided heaps are descending in radius size, and the drones are descending by size of the area covered. We have Si as the area of the ith heap, pi as the area covered by the ith drone. We compare the sorted heaps to the drones one by one, and when Si > Pi, return TRUE, K plus one, and continue to heap.

```c++
bool jude () {
    for (int i=0; i<K; i++)
        if(S[i]<=P[i]) continue;
    else return false;
}
return true;
```
3. Organization of the Tex

3.1. The heap effect diagram is shown in Figure 2.

3.2. Change different variables to test the accuracy and feasibility of the algorithm.
   (1) The same number of drones deployed under different distributions (X-person matrix scenario number, Y-required number of drones), as shown in Figure III.
   (2) Drone deployment scenarios for different numbers (X-number, Y-required number of drones), as shown in Figure IV.
   (3) Drone deployment scenarios under different drone numbers (X-existing number of drones, Y-number of drones sent), as shown in Figure V.

![Figure 2. UAV distribution](image1)

![Figure 3. The number of UAVs required varies with the population distribution](image2)
4. Conclusions
In this paper, we optimize the traditional K-Means clustering problem. With the traditional K-Means clustering algorithm, there is no limit to the number of people per pile in the clustering results. But for the real-life deployment of drones, each drone coverage capacity is different, and the well-divided pile must be less than equal to the coverage area of the drone, which requires us to optimize the traditional K-Means algorithm to achieve the goal.

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