An UAV-based incentive mechanism for Crowdsensing with budget constraints

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***Abstract*—Monitoring environmental variables in lower layers of the atmosphere is an important activity to measure changes that result from natural events, and human interventions. Volcano eruptions, commercial aviation, and the massive spread of pesticides using light aircraft are just some examples of low layer atmosphere polluters. Twice a day, every day of the year, weather balloons are released simultaneously from almost 900 locations worldwide to monitor environmental variables. The flight of these synthetic rubber balloons last for around 2 hours, then they become pollution too. Recent advances in small unmanned aerial vehicles (UAVs) with built in sensors, and their emerging role in business supply chain make UAVs ideal participants for environmental monitoring. In this paper, we present an incentive mechanism for UAV-Crowdsensing. The core of the proposed mechanism consists of a recurrent reverse action and a recruitment model. By these two components, the system encourages UAVs sensing from locations that maximize volume coverage within a given budget. Through extensive simulations, we evaluate the performance of the proposed incentive mechanism.**

***Index Terms*—Crowdsensing, UAV, Coverage, Drones**

I. Introduction

Swarm Robotics (SR) is part of the autonomous robotics area, where huge groups of robots work collaboratively trying to accomplish a specific task. The robot group is made up of a large number of agents or robots which are simple machines with basic behaviors and deploying simple skills, although cooperation among these agents accomplishes complex tasks working in a decentralized manner.

SR plays an important role in the development of collective artificial intelligence. SR promises to be efficient in several application areas such as search and rescue in disaster zones [3], [10], supply chain management, precision agriculture, remote sensing, surveillance, last-mile package delivery, and an ample number of military applications among others.

In recent years the development of unmanned aerial vehicles (UAV) has increased exponentially and this development begins to make real the idea of having drone-based cooperative robotics physical systems. With a group of aerial robots working cooperatively similar to a swarm, most of the expected tasks can be developed for the cooperative robotics systems previously mentioned and, at the same time, develop remote sensing missions, specifically for this case UAV-Crowdsensing given the great number of agents that would make up the Swarm.

The specific example that we treat for UAV-Crowdsensing is the case where you can perform monitoring of environmental variables that can give information on important changes in the lower layer of the atmosphere, such changes can be the product of natural events or human intervention. Changes caused by forest fires, volcanic eruptions, excessive use of pesticides through the use of aircraft are some of the examples that make the sensing of different atmospheric variables necessary. The great advantage of UAV-Swarm is that they can carry out tasks of UAV-Crowdsensing while performing search and rescue tasks in cases of natural disasters or forest fires, surveillance or transport missions and delivery of goods. This last task has taken great importance in recent years thanks to the strong support that is receiving from large retail corporation

II. Literature Review

In recent years the development of UAVs has increased exponentially and with them the approach of solutions based on the use of this type of autonomous robot. At the same time and with the evolution of wireless communication networks, the solutions based on Crowdsensing have increased and these have attracted the interest of researchers and industry. Crowdsensing is highly attractive because of the amount of data that is possible to collect thanks to the use of cellphones and smart vehicles, although currently most of the designs are based on the use of smartphones. Some works show the great variety of applications that can be developed with the advent of UAVs as [11] where a crowd surveillance system based on UAVs network is proposed. The system is approached surveillance using face recognition technology. The use of UAV Swarm for civilian applications is proposed by [1], where a network based on UAVs is used for computer vision applications and communication systems support. As this work depicts the future of the UAVs swarm is great and full of huge variety of applications. Another work as depicted in [5] drive the roll of wireless sensor network for UAVs in natural disaster management missions. This work establishes the idea that UAVs can perform secondary tasks in the way to improve the performance of the primary UAVs team mission.

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In contrast to the previously described works where the UAV swarm develops specific missions, our approach aims at the execution of Crowdsensing tasks in the background and in parallel to primary tasks such as surveillance, natural disaster assistance, last-mile delivery, and monitoring among others. Other works raise the development of tasks directly related to the Crowdsensing mission and the establishment of mobile communication networks. As the work described by Zhou et al., in [14] is approaching in a similar way than our work. They face the possibility of mobile Crowdsensing improvement through the use of UAVs. This work deals with the issue of path planning, energy-efficient, and task assignment for an agent into a group of UAVs. Those issues are resolved using technics based on dynamic programming, genetic and Gale-Shapley algorithms. The work described in [13] is a great example where a possible dangerous gas level is inspected in the way to determine the best route to evacuate people and reduce the possible casualties, UAV is an excellent tool for Crowdsensing applicable to rescue people. They are proposing a policy to optimize the evacuation route, however, the Crowdsensing if a primary task. In [2] depicts a work facing the problem of no collaborative and dishonest vehicles been members of a Crowdsensing network. This work proposes the use of UAVs network working in a collaboration with ground vehicles and Road Side Unites (RSUs). The entire system is evaluated in urban environments. The proposed solution offers crowd and trust traffic information, high packet delivery ratios with low overhead, however, the optimization coverage and budget minimization in the Crowdsensing behavior is not worked in it. In a similar way proposed by our work, a crowded network based on UAVs interaction is proposed by [2], however, this work approach is based on a probabilistic estimation of the user position with an aim to ensure network connectivity, the system uses a potential field method. Finally, A complete network interaction is proposed [4] where a system called AGMEN (Air-Ground integrated Mobile Edge Network). This system propose the use of UAVs with network generation and interaction among them and a ground network conformed by ground stations working as a control center and mobile vehicles connected to the ground network. This project proposed the complete Crowdsensing system based on the interaction between the UAV network and a ground vehicle network. Additionally, this research proposed as a challenge, design policies to optimize the Crowdsensing network and data collection in a distributed way, as we are proposing in this work. Unlike the vast majority of the works focused on UAVs Crowdsensing, our work proposes the development of Crowdsensing tasks in the background while UAV team develops a primary task. Additionally, we propose a system for coverage area maximizing and sample cost-minimizing through the use of limited budget ensuring the participation of all members of the robot team in the auction scheme.

III. System Model

In this section we present the elements of our proposed incentive mechanism and how these elements are related to each other. The following are the main elements of our system: A space region of sensing interest, a set of UAVs going from starting locations to destinations, a geometrical model of sensing range, a crowdsourer or data buyer, and a participant recruitment mechanisms.

A. Participants

Our designed UAVs crowdsourcing problem consists of multiple participants (UAVs) and a crowdsourcer. The crowdsourcer wants to acquire sensing samples across a set of space sub regions $G = \{g_1, g_2, \ldots, g_K\}$ of interest. The crowdsoucer runs a reverse auction to encourage UAVs to collect data and bid or offer their collected sensing samples. Let $V = \{v_1, v_2, \ldots, v_M\}$ be the set of M UAVs. Also, let $S = \{s_1, s_1, \ldots, s_M\}$ and $D = \{d_1, d_2, \ldots, d_M\}$ represent the sets of starting and destination space regions for UAVs.

B. Geometrical Model and coverage

We propose to cover a space region of sensing interest by using a sphere geometric model. Equation 1 shows our geometrical coverage approach.

$$f(d(UAV_i, UAV_j))) = \begin{cases} 1 & \text{if } d(UAV_i, UAV_j) \leq R \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

Where, $d(UAV_i, UAV_j)$ corresponds to the euclidean distance between a sensor in UAV_i which is defined as the center of a sphere and a sensor in UAV_j. if $d(UAV_i, UAV_j) \leq R$, we said that UAV_j is covered by UAV_i. Otherwise UAV_j is out of the sensing range of UAV_i.

Given a region of sensing interest, and a set of UAVs traversing that region. Our goal is to encourage UAVs data collection in order to acquire a set of representative sensing samples from that region using a limited budget.

For that purpose, we use a recurrent reverse auction [9]. At each round t the UAVs bid (offer to sell) for their sensing samples at their current locations. And the platform uses the following sample acquisition method. First, acquire the less expensive sample UAV_i. Once acquired UAV_i we don't acquire any other sample UAV_j, if $d(UAV_i, UAV_j) \leq R$. Once, acquired UAV_i we can assume that we are acquiring the set of samples in the sphere with center in UAV_i, we call this set S_i. Let us define w_i as weight or carnality of S_i, and c_i the cost S_i which corresponds to the cost of of sample acquired from UAV_i. Given the previous notation, now we can state our problem as follows: Given a set U of n elements, a collection $\{S_i\}$, $i = 1, 2, \ldots n$ of subset of S and a budget L, find the subset $S' \subseteq S$ such that the total cost of S' don't exceed L, and the total weight of elements covered by S' is maximized. This NP-hard problem, presented by Kuller [7] is known as the Budgeted Maximum Coverage Problem (BMCP). Thus, we model our sample acquisition policy as a BMCP, next we present the greedy algorithm we use for sample acquisition. This algorithm approximates BMCP with an approximation factor of $(1 + \frac{1}{e})$.

C. Greedy Algorithm sample acquisition and UAVs Space Coverage

Now we present our approach for sensing sample acquisition based on UAV location and sample price. This approach has the form of the following three functions:*Budget optimizer*, *Weight optimizer*, and *Final coverage*.

1) Budget optimizer: Algorithm 1 loops through U (set of all the subset S_i) building a collection of subsets based on the maximization of $\frac{W'}{c_i}$, where W' denotes the total weight of the elements covered by set S_i, but not covered by any set in G. In other worlds, acquires the sets of elements that represent the best value for the paid price c_i within a budget L. Finally, the algorithm return the collection of sets G.

Algorithm 1: Weight optimizer

```
input : S a collection of sets made up by the user locations
output: T ⊆ S, covering set

begin
    G ← ∅
    C ← 0
    U ← S
    T ← ∅
    while U ≠ ∅ do
        select S_i ∈ U that maximizes W'_i / c_i
        if C + c_i ≤ L then
            G ← G ∪ S_i
            C ← C + c_i
            U ← U \ S_i
        end
    end
    return G
end
```

2) Weight optimizer: Algorithm 2 loops through U building a collection of subsets based on the maximization of W', namely the total number of the elements covered by set S_i, but not covered by any set in G. In other words, acquires the sets with the maximum number of covered samples, constrained to the availability of budget L.

Algorithm 2: Weight optimizer

```
Input : S a collection of sets made up by the user locations
output: T ⊆ S, covering set

begin
    G ← ∅
    C ← 0
    U ← S
    T ← ∅
    while U ≠ ∅ do
        select S_i ∈ U that maximizes W'_i
        if C + c_i ≤ L then
            G ← G ∪ S_i
            C ← C + c_i
            U ← U \ S_i
        end
    end
    return G
end
```

Algorithm 3 calls the functions budget optimizer, and weight optimizer. These functions return the collections (set of sets) G, and G' respectively. Thus, the final coverage algorithm returns the collection with the maximum number of elements.

Algorithm 3: Final Coverage

```
Input : S a collection of sets made up by the user locations
output: S' ⊆ S, covering set

begin
    G ← ∅
    G' ← ∅
    S' ← ∅
    G ← Budget-Optimizer()
    G' ← Volume-Coverage-Optimizer()
    if |G| ≥ |G'| then
        S' = G'
    else
        S' = G
    end
    return S'
end
```

D. Coverage

In each round the final coverage algorithm finds a $S' \subseteq S$ that covers the greatest possible area covered by S. In areas where the variable of interest is not uniform distributed Figure 2 and Figure 3 illustrate how works how final coverage works, in the former case the algorithm acquired the first k samples in increasing order of cost, in the latter case the algorithm avoids to choose redundant samples, and rather, choose those less expensive which maximize the coverage. Furthermore, in order to increase the geographical coverage balance and encourage the mobility towards areas that have not been covered previously.

E. participant recruitment mechanisms

We use the recurrent Reverse Auction Based Dynamic Price with Virtual Participation Credit and Recruitment (RADP-VPC-RC) presented by [9], [12] as recruitment mechanism. RADP-VPC-RC work using rounds, thus, at every round t participants offer to sell their sensing samples to the platform. We use RADP-VPC-RC in combination with our greedy algorithm, and our geometric sensing model to acquire the set of samples that cover the space using spheres at minimum cost.

Algorithm 4 sketch the main components of our recruitment approach. Algorithm input include the UAVs bids, the list of UAVs locations, and constant $k > 0$ that updates the value of the virtual participation credit (VC). VC artificially decreases the bid's price of a loser by a constant k, this increases the loser's chances of winning in the next round. Thus, the auctioneer see the bid price as $b_i - k$, but pays b_i.

Here, a UAV bid or offer to collect a sample in its location, and the platform uses Algorithm 3 to select the winner. A winner increases its bid with a 50% of probability for the next round. On the other hand, if the bid is rejected (lose), then the UAV decreases its bid price by a 20%. The VC is update by a constant $VC = VC + k$, and the participant updates its bid again by using the virtual participation credit as follows $b_i^{r*} = b_i^r - v_i^r$. This credit is keeps increasing while the user is losing and as soon as the user wins this value is set to zero. Another, important element of RADP-VPC-RC is Return on Investment (ROI), this indicator is used as criteria to determine when a user is dropping out of the system. The ratio is represented as follow:

$$ROI = \frac{e_i^r + \beta_i}{p_i^r.t_i + \beta_i} \tag{2}$$

Where, e_i^r corresponds to the earned reward by user i until round r. $p_i^r.t_i$, corresponds to the minimum reward, with p_i^r as the number of participation instances of i up to the current auction round r, t_i as the user's true valuation, and β_i as the tolerance period. Every round, the user evaluates their S_i^r value; if it is below a certain threshold then they drop out. In addition, RADP-VPC-RC provides a rejoin mechanism, which allows the auctioneer to communicate the maximum winning price φ_k to the users that dropped out of the system. The knowledge of this price allows the users to re-evaluate their ROI and potentially return to the next auction round. This expected ROI is evaluated as follows:

$$EROI = \frac{e_k^r + \varphi_k + \beta_k}{(p_k^r + 1).t_k + \beta_k} \tag{3}$$

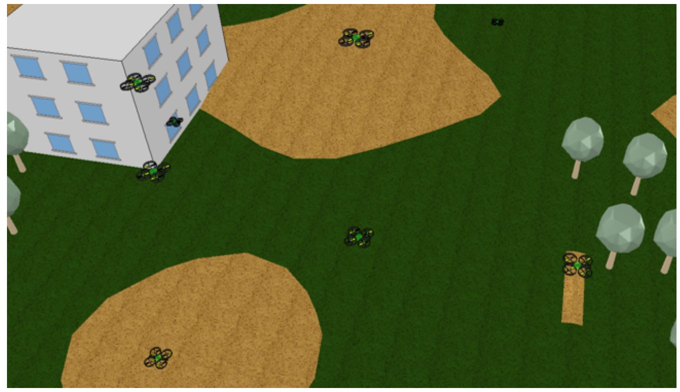
Algorithm 4: participant recruitment mechanisms (PRM)

input : UAVs bid at time t $B = \{b_1^t, b_2^t, \ldots b_M^t\}$, UAVs location $V = \{v_1, v_2, \ldots, v_M\}$, k virtual participation credit constant
output: Participant next bid b_i^{t+1}

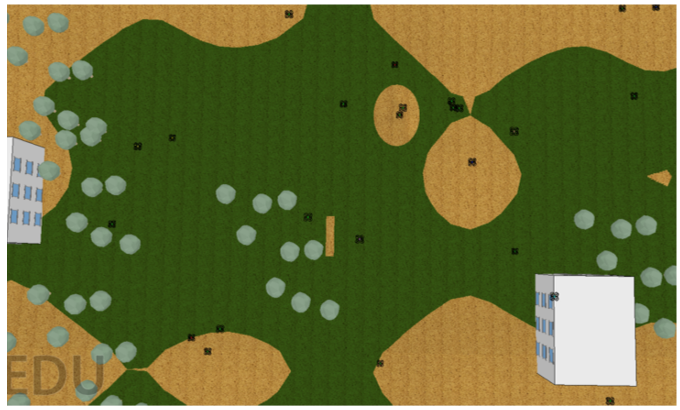
```
begin
    lose ← 0
    drop ← 0
    VC ← 0 /* set virtual participation credit */

    winners ← WeightOptimizer(B, V)
    if b_i^t ∈ winners then
        b_{i+1}^t ← 1.1b_i^t /* increase next bid with 50% of
            prob */

        v_i.update(ROI) /* updates return of investment
            */

        VC ← 0
    else
        /* bid rejected - lose */
        lose ← 1
        v_i.update(ROI)
    end
    if lose == 1 & ROI ≥ 0.5 then
        /* vi_i will bid at round t+1 */
        b_i^{t+1} ← 0.8b_i^t − VP /* update bid price */

        VC ← VC + k
        /* VC update */
    if lose == 1 & ROI < 0.5 then
        /* drops from the auction */
        drop ← 1
        v_i.update(EROI)
    if drop == 1 & EROI ≥ 0.5 then
        /* will re-joint and bid at t+1 with 50% of
            prob */
    if drop == 1 & EROI < 0.5 then
        /* stays out */
    return b_i^{t+1}
end
```

F. Budget

Budget is divided evenly by the number of rounds; however, at the end of each round r_i, if the total amount of budget assigned to round r_i is not used completely. Then, the remaining part, from round r_i, is added to the $r_i + 1$ round.



[a] UAV View



[b] Top View

Fig. 1: UAV multi-normal distribution in space

G. Performance Evaluation

A set of different experiments were designed in order to evaluate the influence of budget on space coverage, and participant retention, finally another experiment is meant to compare sensing coverage when using our acquisition sample policy versus an acquisition policy based on sample price.

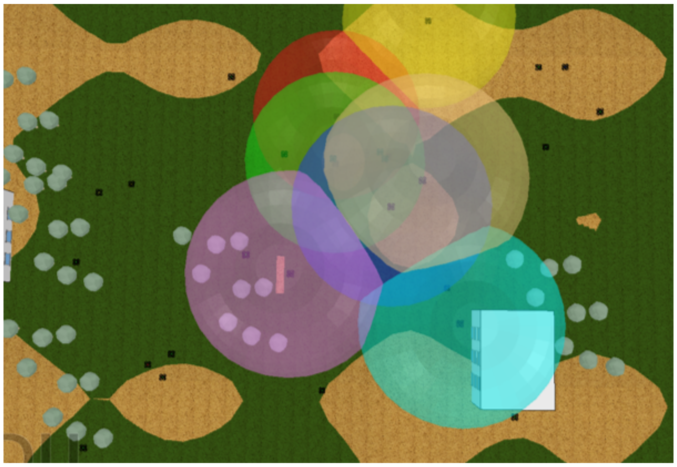
H. Experimental setup

The experiments were developed to evaluate the performance of our system using the Virtual Robotics Environment Platform (VREP). This platform allows virtual model simulations of some commercial physical robots such as Pioneer, NAO, Drones, and Kephera mobile robots among others. The interaction environment was established within a volume of 1'000,000 m^3 with two buildings and a group of trees, in addition to 50 drones as shown in Figure 1 and Table I. These Drones perform a primary surveillance task and in the background execute our mission of UAV-Crowdsensing.

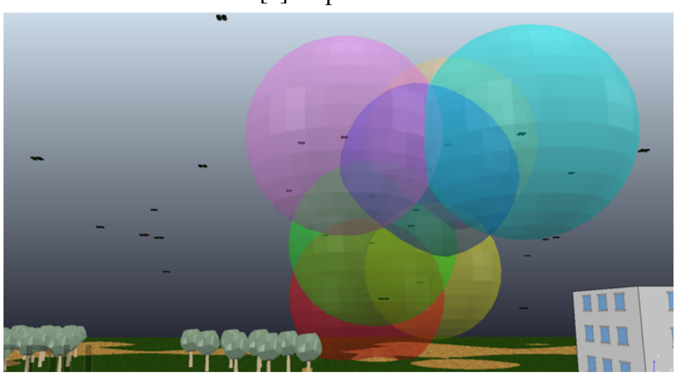
Table I summarizes the simulation parameters for our set of experiments. Here, our sensing space area of interest corresponds to cube of 100mt × 100mt × 100mt. We deployed 50 UAVs, Figure 1 (b) shows top view of the UVAs deployment

TABLE I: Simulation parameters.

Parameters	Experiment 1	Experiment 2	Experiment3
Deployment Volume	100mx100mx100m		
Instances	50		
Location Distr	normal	normal	normal
Bid Distr	normal	normal	normal
Radio	5	5	5
Budget	10:1000	10:1000	10:1000
Beta	(3,7)	(3,7)	(3,7)
Alpha	7	7	7



[a] Top view



[b] Front View

Fig. 2: Normal distributed UAVs in the space.

distribution (normal). UAVs bids' price are normally distributed, the sensor range ($Radius$) for the set of experiment was set to five following the empirical work of [6]. The RADP-VPC-RC parameter Beta random per UAV sampled from a uniform distribution (3,7), and the Alpha parameter was set to 7. Both Beta, and Alpha are parameters of RADP-VPC-RC and were set based on the result of [8].

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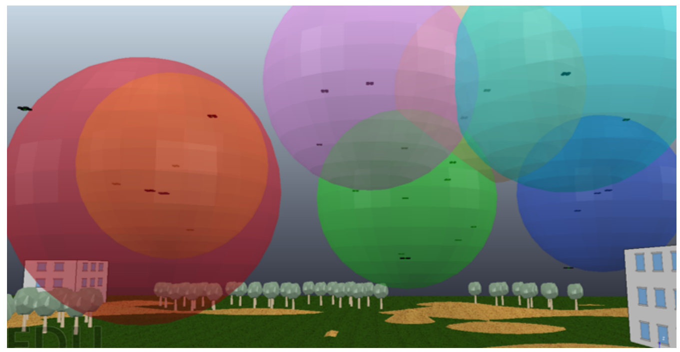
I. Experiment 1: Determining the influence of budget on participant retention

The goal of this experiment is to explore the influence of budget on participants' retention, namely keeping a critical mass of participants in order of keeping the system functional. Figure 4 shows the effect of increasing the budget from 50 to

[a] Top view



[b] Front View

Fig. 3: Coverage based on sample acquisition policy UAV-crowdsensing.

1000. As can be seen as we increase budget we see an almost

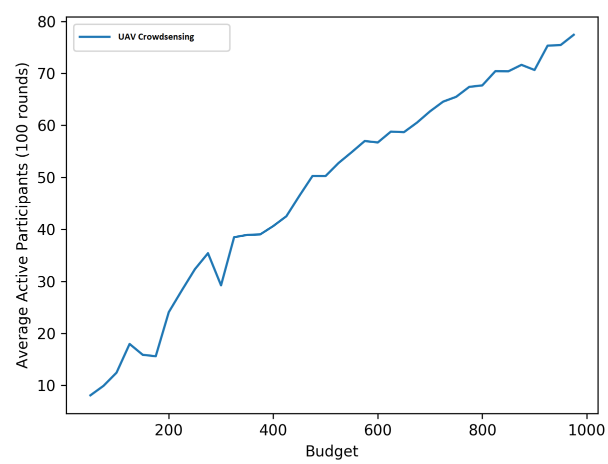


Fig. 4: Budget vs Number of active participants

linear increment in the number of active participant after 100 rounds. Keeping a critical mass of participants is fundamental in crowdsensing. In particular, when recruitment process is based on auction. Lee [9] showed that a common problem in reverse auction is participant dropping from the auction due to participation starvation. This phenomena causes that just a

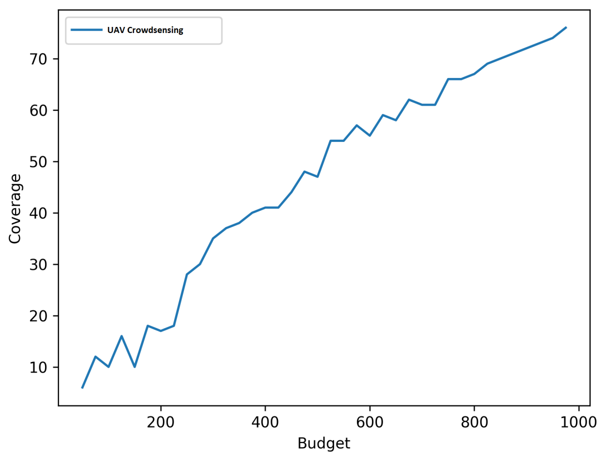


Fig. 5: Budget vs area coverage

small group of winners stay, then they raise the bids' prices without any control given than now there is not competition. Here, this problem is addressed by increasing participants' chances of win. This is done by using a virtual participation credit, and recruitment (RC) component of RADP-VPC-RC.

J. Experiment 2: Exploring the influence of budget on area coverage

The main goal of this experiment is explore the influence of budget of area coverage.

Figure 5 shows that coverage scales very well with increases in budget. This is important because, it is possible to reconstruct the variable of interest by injecting budget. This also shows how our sample acquisition policy based in a combination of location and bid's price is able to cover the area of interest based on spheres.

K. Experiment 3: Comparing our sample acquisition policy with an acquisition policy based on sample price

For this experiment the UAVs bids' sample price are normally distributed, as well as the UAVs location, see Figure 1. Thus, the bids' prices of UAVs located in some clusters are higher than the bid prices of UAVs located in other clusters. This could be the cases of UAVs working from different companies with different bids' price expectations. Figure 2 shows the result of acquiring samples based on the cheapest sample price. Here, the UAVs bids' prices in a cluster are very low, then the platform uses all its budget to acquire these samples. Figure 2 shows the data redundancy that result from acquiring samples in this settings using an acquisition policy based only on sample price. In contrast, Figure-3 shows the coverage that result from acquiring sensing samples now using our data acquisition policy.

IV. Acknowledgements

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V. Conclusion and Future Work

This paper presents an UAV-based incentive mechanism for Crowdsensing with budget constraints. Comprehensive simulations are presented to evaluate the performance of the proposed approach. By using extensive simulations we show how proposed sample acquisition policy outperforms an acquisition policy based on sample price. The work shows desirable characteristics in terms of number of active participants, and improvements in space coverage.

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