A Truthful Mechanism For Mobility Management In Unmanned Aerial Vehicles Networks

Baocheng Geng
Department of EECS
Syracuse University
Syracuse, USA
bageng@syr.edu

Swastik Brahma
Department of Computer Science
Tennessee State University
Nashville, USA
brahma@Tnstate.edu

Pramod K. Varshney
Department of EECS
Syracuse University
Syracuse, USA
varshney@syr.edu

***Abstract*—We study the task allocation strategy in a UAV swarm sensing platform for performing location estimation. In particular, we design a reverse auction mechanism where the fusion center (FC) selects a subset of UAVs, and instructs them to move to particular positions to take measurements regarding a target. Based on the measurements, the FC estimates the location of the target and reimburses the UAVs for their participation in performing the sensing tasks. The auction mechanism addresses participatory concerns of the UAVs that arise due to energy consumption, while ensuring that the UAVs truthfully report their participation costs. Our mechanism maximizes the utility of the FC to achieve desired sensing objectives and numerical results are provided for illustration.**

I. Introduction

Unmanned aerial vehicles (UAVs) are widely being used in target localization due to their flexibility of movement and the ability to fly over dangerous and inaccessible areas [1], [2]. Embedded with global positioning system (GPS) and different kinds of electronic sensors, UAVs can move to desired regions of interest (RoI) and take measurements regarding the target. Since a single UAV has limited coverage, battery capacity and processing ability, it is advantageous to deploy a swarm of UAVs to work together. Multi-UAV-localization is gaining fast popularity. For example, a multiple-UAV cooperative path planning technique was proposed to solve problems of target tracking and obstacle avoidance [3]. The authors developed a UAV swarm network using low cost sensors which can perform distributed cooperative localization [4].

However, most of the literature assumes voluntary participation of UAVs in sensing tasks without addressing their selfish concerns. Since a UAV consumes power/energy to take measurements [5], it requires incentives to be motivated to perform the sensing tasks and provide its sensing measurements. This concern becomes more relevant when UAVs in the network belong to different organizations or individuals.

There has been some work on incentive mechanism design in networked UAV-collaborative systems. In [6], the authors considered the selfish concerns of UAVs and analyzed their strategic behavior in trajectory planning and coalition formation. A decentralized planning algorithm that relies on an auction scheme was developed to plan finite look-ahead paths for multiple UAVs [7]. However, these auction-based mechanism designs for swarms of UAVs rely heavily on the participant's truthful revelation of their bids. The bids, representing the UAVs' personal information while performing the sensing task, reflect their costs of participation. In such a scenario, if the auction mechanism is not truthful (or, in other words, strategy-proof), some UAVs might intentionally falsify their bids in order to gain undue advantages. Untruthful mechanisms suffer from low economic efficiency and are prone to market manipulations [8].

The authors of [9]–[11] have developed incentive mechanisms that ensure truthful revelation of bids, but without formulating the mobility strategy of the participants. Therefore, these mechanisms are not applicable to the scenario of UAV swarm sensing, where the most prominent feature is the ability of UAVs to move to specified locations. When the mobility of UAVs is considered, the problem is much more challenging as we not only need to select a group of UAVs to take measurements regarding the target, but we also need to determine where the selected UAVs should move to. As a UAV moves closer to the target, the quality of the measurement becomes better. Therefore, the trade-off between the quality improvement of the measurement and the energy consumption due to movement must be considered. The problem is further complicated by the fact that participants may intentionally falsify the bids in order to gain additional advantages.

The contribution of this work is to design an auction-based mobility management mechanism for UAVs that ensures truthful revelation of participation costs, which, to the best of our knowledge, has not been addressed in the literature. We study target localization using the received power measurements from the UAVs. Initially each UAV sends a bid representing its cost per unit energy to the FC. After the FC receives these bids, to maximize its own benefit, it selects a subset of UAVs to take measurements and at the same time, determines the positions they should move to. Finally, the FC estimates the position of the target and makes payments to the UAVs. Our mechanism is optimal in the following sense: i) the FC's utility is maximized; ii) each UAV has non-negative expected utility, making their participation in the mechanism rational; and iii) the UAVs do not benefit from falsifying their bids to the FC, i.e. incentive-compatibility condition is satisfied.

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II. PROBLEM SETUP

In this section, we present our system model considering the problem of localizing a single target. For simplicity of notation, we assume that the swarm of UAVs, the target and the FC are of the same height so the problem can be formulated in 2D space (our system model can be easily extended to 3D space). There are N UAVs $s_1, s_2, \ldots, s_N$ uniformly deployed in the region of interest (RoI). The location of the i^{th} UAV is denoted as $l_i : (x_i, y_i)$, which is assumed to be known to the FC. The target is located at an unknown position $l_t : (x_t, y_t)$ and it emits power that attenuates as a function of distance. The FC, located at $l_{fc} : (x_{fc}, y_{fc})$, collects measurements from UAVs and makes an inference about the target's location. We consider the RoI to be divided into a grid consisting of $j = 1, 2, \ldots, J$ cells.

Following the power attenuation model described in [12], the i^{th} UAV located at l_i receives the signal power $z_i = \sqrt{\dfrac{P_0}{1+\alpha \left\|l_i - l_t\right\|_2^2}} + n_i \triangleq a_i + n_i$, where P_0 is the signal power emitted by the target and α is a scaling parameter. n_i represents the additive noise in the measurement and is assumed to be independent Gaussian noise that follows the normal distribution $\mathcal{N}(0, \sigma^2)$. We consider that each UAV sends Z_i to the FC by quantizing its measurement z_i to m bits, such that

$$Z_i = \begin{cases} 0 & -\infty < z_i < \eta_1 \\ \vdots & \\ R-1 & \eta_{R-1} \le z_i < \infty \ , \end{cases}$$

where $\eta_1, \ldots, \eta_{R-1}$ are uniform quantization levels and $R = 2^m$ is the number of quantization levels of each UAV. Given the target location l_t and the i^{th} UAV's location l_i, the probability that Z_i equals r is $p(Z_i = r|l_i, l_t) = Q(\frac{\eta_r - a_i}{\sigma}) - Q(\frac{\eta_{r+1} - a_i}{\sigma})$, where $Q(\cdot)$ is the complementary distribution of the standard normal distribution. Assume that different UAVs take measurements independently, the joint probability density function (PDF) of the quantized measurements $Z = (Z_1, \ldots, Z_N)$ is:

$$p(Z|l_i, l_t) = \prod_{i=1}^{N} p(Z_i|l_i, l_t) \tag{1}$$

The energy consumption of a UAV consists of two parts. One part of energy consumption takes place when a UAV moves from one cell to another, $E_i^M = \phi \times \|l_i' - l_i\|_2$, where l_i' and l_i are the initial position and the final position of the UAV, respectively. ϕ is the energy needed for the UAV to move a unit distance[1]. The other part is the energy needed to transmit the m-bit measurement to the FC, $E_i^T = \epsilon \times m \times \|l_i - l_{fc}\|_2^2$, where ϵ is the energy needed in data transmission per bit per unit distance square[2].

[1]When the sensing nodes are static, their energy consumption due to movement, E_i^M for $i = 1, \ldots, N$, is fixed to be 0, which can be treated as a special case of our UAV-sensing model that allows mobility.

[2]In experiments conducted in [5], the energy consumption for short distance communication is negligible compared to UAV movement. More generally, E_i^T in our model represents the energy needed for data processing including signal reception, quantization and transmission.

A. Location estimation and information gain

After the FC collects measurements from a subset of UAVs, it uses an importance sampling based particle filter approach to estimate the location of the target. A particle filter is based on Monte-Carlo simulations and it represents the target's posterior distribution $p(l_t|Z)$ using a group of particles t_s and the associated weights w_s [13]:

$$p(l_t|Z) \approx \sum_{s=1}^{N_s} w_s \delta(l_t - t_s) \tag{2}$$

where a total of N_s particles $t_s, s \in \{1, 2, \ldots, N_s\}$ are generated according to the prior distribution of the target's location; the weight of each particle w_s is updated in proportion to the likelihood function (1); and $\delta(\cdot)$ is the Dirac delta function. When N_s is large enough, the representation of (2) is very close to the posterior distribution of the target's location.

Next, we introduce measures that characterize the FC's estimation performance and the information gain from each of the UAV. The Cramer-Rao Lower Bound (CRLB) gives the theoretical performance limit for Bayesian estimation [14]. Suppose $\tilde{l}_t$ is the estimator of the target's location l_t, then the CRLB can be expressed as $E\{[\tilde{l}_t - l_t][\tilde{l}_t - l_t]^T\} \ge \mathcal{F}^{-1}$, where $\mathcal{F}$ is the inverse of the CRLB and is known as the Fisher information (FI) matrix. It is desirable to minimize $\mathcal{F}^{-1}$ to reduce the estimation error. However, calculating $\mathcal{F}^{-1}$ requires a lot of computation and authors in [15] provide a surrogate approach that maximizes the trace of the FI matrix $\mathcal{F}$. Furthermore, the FI matrix can be decomposed into two parts: the FI obtained from the UAVs' measurements and the FI from the prior information of the target's location: $\mathcal{F} = \mathcal{F}^D + \mathcal{F}^P$. It was shown that since each UAV takes its measurement independently, the FI matrix from the measurements of a total of N UAVs can be written as: $\mathcal{F}^D = \sum_{i=1}^N \int_{l_t} \mathcal{F}_i^D p(l_t) dl_t$, where $p(l_t)$ is the prior knowledge of the target's location distribution, and $\mathcal{F}_i^D = \int_{z_i} \frac{1}{p(z_i|l_i,l_t)} \left(\frac{\partial p(z_i|l_i,l_t)}{\partial l_t}\right)^2 dz_i$ is the FI matrix of the i^{th} UAV [16]. We use $I_i^D = tr\left(\int_{l_t} \mathcal{F}_i^D p(l_t) dl_t\right)$, where $tr(\cdot)$ is the matrix trace, to represent the information contribution of the i^{th} UAV in estimating the location of the target. The larger I_i^D is, the more information the i^{th} UAV contributes towards the estimation of the target's location. Let $I^P = tr(\mathcal{F}^P)$ be the information from the prior knowledge of the target, and the total information gain can be written as $I = tr(\mathcal{F}) = \sum_{i=1}^N I_i^D + I^P$.

B. Auction-based mobility management

We describe our auction mechanism and formulate the optimization problem for the FC in this subsection. At the beginning of our mechanism, each UAV (bidder) sends a bid v_i to the FC (auctioneer), where v_i represents bidder i's valuation of cost per unit energy. Afterwards, the FC selects a subset of UAVs to take measurements regarding the target and reimburses them for their energy consumption in performing the sensing task. Because of the selfishness of the UAVs, the UAVs' utilities in participating in the sensing task should be nonnegative, i.e., the payments are no smaller than their costs due to energy consumption. We assume that the UAVs always choose to participate when their utilities are nonnegative with the UAVs competing to sell their measurements to the FC.

Before the bidders report their bids, only UAV i knows its true bid, and for other bidders and the FC who are uncertain about v_i, v_i follows a PDF $f_i(v_i) : [a_i, , b_i] \rightarrow R^+$, where a_i and b_i are bidder i's lowest and highest bid, respectively. Let $\boldsymbol{v} = (v_1, v_2, \ldots, v_N)$ denote the vector that contains bids from all the UAVs. Suppose that the bid of each UAV is statistically independent of each other. Therefore, the FC's uncertainty about $\boldsymbol{v}$ can be expressed as the joint PDF $f^v(\boldsymbol{v}) = \prod_{k=1,\ldots,N} f_k(v_k)$. For bidder i, the joint PDF of all other bidders' bid $\boldsymbol{v}_{-i} = (v_1, \ldots, v_{i-1}, v_{i+1}, \ldots, v_N)$ can be written as $f^v_{-i}(\boldsymbol{v}_{-i}) = \prod_{k=1,\ldots,i-1,i+1,\ldots,N} f_k(v_k)$.

We consider the FC to derive a benefit from estimating the location of the target and its valuation per unit Fisher information gain is considered to be v_{FC}. We assume that v_{FC} is known to all the bidders. In our mechanism, the FC is assumed to instruct the selected UAVs to move to the center of particular cells. The location of the j^{th} cell's center is denoted as o_j. Based on the analysis of Section II.A, the FI matrix provided by the i^{th} UAV when it moves to the center of j^{th} cell is: $F^D_{ij} = \int_{Z_i} \frac{1}{p(Z_i|o_j, l_t)} \Big(\frac{\partial p(Z_i|o_j, l_t)}{\partial l_t}\Big)^2 dZ_i$. Let $I^D_{ij} = tr(F^D_{ij})$ be the information gain of the measurement taken by the i^{th} UAV when it moves to the j^{th} cell.

Given the UAVs' bid vector that represents their energy cost $\boldsymbol{v} = (v_1, v_2, \ldots, v_N)$, the FC's objective is to select a subset of UAVs and determine which cells these UAVs should move to, so as to maximize its expected utility in estimating the target's location. After the selected UAVs move to the instructed cells, they take measurements regarding the target and send the quantized measurements to the FC. Finally, the FC makes payments to the UAVs for their participation in the sensing task.

Now we formulate the auction-based mobility management problem. The outcome of the auction mechanism can be described by a pair of functions $(\mathbf{p}, \mathbf{q})$ where $\mathbf{q}(\boldsymbol{v}) = [q_{11}, q_{12}, \ldots, q_{1J}; \ldots; q_{N1}, q_{N2}, \ldots, q_{NJ}]$ such that $q_{ij}(\boldsymbol{v}) \in \{0, 1\}$ is the decision variable that represents whether or not the FC selects the i^{th} UAV and instructs it to move to the j^{th} cell; and $\mathbf{p}(\boldsymbol{v}) = [p_1, \ldots, p_N]$ such that $p_i(\boldsymbol{v})$ is the payment FC makes to the i^{th} UAV. We allow for the possibility that the FC might have to pay something to a UAV even if that UAV is not selected.

The utility functions of the FC and the UAVs are their expected gains minus their expected incurred costs. Let $V = [a_1, b_1] \times \cdots \times [a_N, b_N]$ represent the set of all possible combinations of the UAVs' bid vector. The expected utility of the FC can be expressed as:

$$\mathcal{U}^{FC}(\mathbf{p}, \mathbf{q}, \boldsymbol{v}) = \int\limits_{\boldsymbol{v}\in V} \left[v_{FC}\left(\sum_{i=1}^{N}\sum_{j=1}^{J} q_{ij}(\boldsymbol{v}) I^D_{ij} + I^P \right) - \sum_{i=1}^{N} p_i(\boldsymbol{v}) \right] f^v(\boldsymbol{v}) d\boldsymbol{v} \quad (3)$$

The i^{th} UAV only knows its own cost v_i, without knowing the bids of other UAVs. Therefore, its expected utility $\mathcal{U}_i(v_i, \boldsymbol{v}_{-i})$ is averaged over all possible combinations of $\boldsymbol{v}_{-i}$:

$$\mathcal{U}_i(v_i, \boldsymbol{v}_{-i}) = \int\limits_{\boldsymbol{v}_{-i}\in V_{-i}} \Big[p_i(v_i, \boldsymbol{v}_{-i}) - v_i E_i(v_i, \boldsymbol{v}_{-i}) \Big] f^v_{-i}(\boldsymbol{v}_{-i}) d\boldsymbol{v}_{-i} \quad (4)$$

In the above equation, $E_i(\boldsymbol{v})$, which is short for $E_i(q_{ij}(\boldsymbol{v}))$, is the expected energy consumption of the i^{th} UAV when it moves to all possible J cells in the RoI:

$$E_i(\boldsymbol{v}) = \sum_{j=1}^{J} E^T_{ij} q_{ij}(\boldsymbol{v}) + \sum_{j=1}^{J} E^M_{ij} q_{ij}(\boldsymbol{v}) \triangleq \sum_{j=1}^{J} E_{ij} q_{ij}(\boldsymbol{v}) \quad (5)$$

where $E^T_{ij} = \epsilon \times m \times \|o_j - l_{fc}\|_2^2$ is the energy needed to transmit quantized measurements to the FC when the i^{th} UAV is at the center of cell j, and $E^M_{ij} = \phi \times \|o_j - l'_i\|_2$ is the energy needed for the i^{th} UAV to move to the j^{th} cell from its initial position. In (5), we define $E_{ij} = E^T_{ij} + E^M_{ij}$ to be the total energy consumption when the i^{th} UAV moves to the j^{th} cell and transmits its measurement to the FC.

Because the i^{th} UAV's bid is not known to the FC, it may strategically lie about the bid in order to gain additional benefits. For example, if the i^{th} UAV reports a higher bid than its true valuation, the payment it receives might be higher because the FC *thinks* it has more cost per unit energy. Again, a lower than truthful bid might result in better chances for a UAV to be selected by the FC to take measurements. In the case that an UAV falsifies its bid, i.e., it announces $\tilde{v}_i$ to be its bid when the actual cost per unit energy is v_i, its expected utility $\tilde{\mathcal{U}}_i$ would be:

$$\tilde{\mathcal{U}}_i(\tilde{v}_i, \boldsymbol{v}_{-i}) = \int\limits_{\boldsymbol{v}_{-i}\in V_{-i}} \Big[p_i(\tilde{v}_i, \boldsymbol{v}_{-i}) - v_i E_i(\tilde{v}_i, \boldsymbol{v}_{-i}) \Big] f^v_{-i}(\boldsymbol{v}_{-i}) d\boldsymbol{v}_{-i} \quad (6)$$

To ensure that the mechanism is truthful, i.e., a UAV does not gain extra benefits from lying about its bid, we force $\mathcal{U}_i(v_i, \boldsymbol{v}_{-i}) \geq \tilde{\mathcal{U}}_i(\tilde{v}_i, \boldsymbol{v}_{-i})$.

Thus, the auction-based mobility management problem can be formulated as the following optimization problem:

$$\underset{\mathbf{p},\mathbf{q}}{\text{maximize}} \quad \mathcal{U}^{FC}(\mathbf{p}, \mathbf{q}, \boldsymbol{v}) \quad (7)$$

subject to the constraints: $\mathcal{U}_i(v_i, \boldsymbol{v}_{-i}) \geq 0$ (7a), $\mathcal{U}_i(v_i, \boldsymbol{v}_{-i}) \geq \tilde{\mathcal{U}}_i(\tilde{v}_i, \boldsymbol{v}_{-i})$ (7b), $\sum_{i=1}^{N}\sum_{j=1}^{J} q_{ij}(\boldsymbol{v}) \leq M/m$ (7c), $q_{ij}(\boldsymbol{v}) \in \{0, 1\}$ *and* $\sum_{j=1}^{J} q_{ij}(\boldsymbol{v}) \in \{0, 1\}$ (7d), for $i = \{1, \ldots, N\}$, $j = \{1, \ldots, J\}$. Constraint (7a) ensures that each UAV has a non-negative utility in performing the sensing task, i.e. individual rationality (IR). (7b) is the incentive-compatibility (IC) constraint which guarantees no UAV benefits from lying about its true bid, and (7c) says that due to the communication bandwidth being limited to M bits, a maximum of M/m UAVs can transmit measurements to the FC. (7d) requires that the decision variable has to be a Boolean value.

III. UAV MOBILITY MANAGEMENT

We solve the optimization problem (7) and construct the UAV mobility strategy in this section. In particular, the optimization problem is simplified via the following theorem.

Theorem 1. *The FC can determine the optimal set of UAVs to sense the target and their optimal locations by solving:*

$$\underset{\mathbf{q}}{\text{maximize}} \quad \int_{\boldsymbol{v}\in V} \mathcal{Y}(\mathbf{q},\boldsymbol{v}) f^{v}(\boldsymbol{v}) d\boldsymbol{v} \tag{8}$$

$$\text{subject to} \quad \sum_{i=1}^{N}\sum_{j=1}^{J} q_{ij}(\boldsymbol{v}) \leq M/m, \tag{8a}$$

$$q_{ij}(\boldsymbol{v}) \in \{0,1\} \text{ and } \sum_{j=1}^{J} q_{ij}(\boldsymbol{v}) \in \{0,1\} \tag{8b}$$

where $\mathcal{Y}(\mathbf{q},\boldsymbol{v}) = v_{FC}\{(\sum_{i=1}^{N}\sum_{j=1}^{J} q_{ij}(\boldsymbol{v}) I_{ij}^{D} + I^{P})\} - \sum_{i=1}^{N} E_i(\boldsymbol{v})\left(v_i + \frac{F_i(v_i)}{f_i(v_i)}\right)$, $F_i(v_i) = \int_{a_i}^{v_i} f_i(u_i)du_i$, *and the payment to each UAV* i *is given by:*

$$p_i(\boldsymbol{v}) = v_i E_i(\boldsymbol{v}) + \int_{v_i}^{b_i} E_i(r_i, \boldsymbol{v}_{-i}) dr_i \tag{9}$$

Proof: The main idea is to rewrite the IR constraint (7a), the IC constraint (7b), and substitute them into the optimization problem. Detailed proof will not be provided here due to page limits. ■

Based on above results, we now present how the FC can optimally select UAVs and determine their locations (i.e., how to determine $\boldsymbol{q}(\boldsymbol{v})$), and find the payments of the UAVs (i.e., how to determine $\boldsymbol{p}(\boldsymbol{v})$). Substituting (5) into $\mathcal{Y}(\mathbf{q},\boldsymbol{v})$ of Theorem 1, we have $\mathcal{Y}(\mathbf{q},\boldsymbol{v}) = \sum_{i=1}^{N}\sum_{j=1}^{J} q_{ij}(\boldsymbol{v})\left[v_{FC}I_{ij}^{D} - E_{ij}\left(v_i + \frac{F_i(v_i)}{f_i(v_i)}\right)\right] + v_{FC}I^{P}$. By defining:

$$G_{ij} = v_{FC}I_{ij}^{D} - E_{ij}\left(v_i + \frac{F_i(v_i)}{f_i(v_i)}\right), \tag{10}$$

the optimization problem obtained in Theorem 1 can be written as:

$$\underset{\mathbf{q}}{\text{maximize}} \int_{\boldsymbol{v}\in V} \sum_{i=1}^{N}\sum_{j=1}^{J} \left[G_{ij} q_{ij}(\boldsymbol{v})\right] f^{v}(\boldsymbol{v}) d\boldsymbol{v} \tag{11}$$

subject to the constraints (8a) and (8b). This problem can be solved by choosing $q_{ij}(\boldsymbol{v})$ so that $\sum_{i=1}^{N}\sum_{j=1}^{J}[G_{ij}q_{ij}(\boldsymbol{v})]$ is maximized. First, we calculate the entire set $\{G_{ij} | i \in \{1,2,\ldots,N\},\ j \in \{1,2,\ldots,J\}$. Then, we rank elements in this set in a decreasing order and select the highest M/m entries with distinct i indices. For each of these entries, if G_{ij} is positive, we set the corresponding $q_{ij} = 1$. Note that to maximize the term $\sum_{i=1}^{N}\sum_{j=1}^{J}[G_{ij}q_{ij}(\boldsymbol{v})]$, we discard the entries with negative values of G_{ij}. Algorithm 1 formally provides the procedure for UAV mobility management.

The payment to each UAV i is obtained via (9). Since $E_i(r_i, \boldsymbol{v}_{-i})$ represents the expected energy consumption of the i^{th} UAV when its bid is r_i and all other UAVs' bid vector is $\boldsymbol{v}_{-i}$, it is possible that $E_i(r_i, \boldsymbol{v}_{-i})$ has different values when $r_i \in [v_i, b_i]$. We calculate (9) using numerical methods and the detailed procedure is presented in Algorithm 2.

Algorithm 1 UAV Management: Movement Strategy

PROCEDURE: Determine UAV movement strategy.
Calculate G_{ij} defined in (10), for $i = 1,2\ldots,N$ and $j = 1,2\ldots,J$.
Rank the list of $G_{ij}, i \in \{1,2\ldots,N\}, j \in \{1,2\ldots,J\}$ in the decreasing order.
for $K = 1,2\ldots,M/m$ **do**
  Select the largest $G_{i'j'}$.
  if $G_{i'j'} > 0$ **then**
    Set the corresponding $q_{i'j'} = 1$.
  end if
  Delete all entries associated with the i'^{th} UAV $G_{i'j}, j \in \{1,2\ldots,J\}$ from the list.
end for
Set all other entries of $q_{ij} = 0$.
For each $q_{i'j'} = 1$, the FC selects the i'^{th} UAV and instructs it to move to the j'^{th} cell.

Time complexity: $\mathcal{O}(NJ)$

Algorithm 2 UAV Management: Payment Strategy

PROCEDURE: Determine payment to the i^{th} UAV.
Initialize $p_i = 0$, $r_i = b_i$.
Choose stepsize ϵ.
while $r_i > v_i$ **do**
  Calculate $E_i(r_i, \boldsymbol{v}_{-i})$ based on $\boldsymbol{q}(r_i, \boldsymbol{v}_{-i})$, which is obtained from Algorithm 1.
  Update $p_i = p_i + \epsilon E(r_i, \boldsymbol{v}_{-i})$.
  Update $r_i = r_i - \epsilon$
end while
$p_i = p_i + v_i E_i(\boldsymbol{v})$.
The FC makes payment p_i to the i^{th} UAV.

Time complexity: $\mathcal{O}(\frac{b_i - v_i}{\epsilon} J)$

IV. Simulation Experiments

We evaluate the performance of our mechanism while performing target localization. A swarm of UAVs is uniformly deployed in the RoI of area $d^2 = 50 \times 50\ m^2$. The prior distribution about the target location, $p(l_t)$, is assumed to be Gaussian with mean $\boldsymbol{\mu}_0 = [-3 \ \ -3]^T$ and covariance $\boldsymbol{\Sigma}_0 = \text{diag}[\sigma_{\mathbf{t}}^2 \ \sigma_{\mathbf{t}}^2]$ where we select $\sigma_{\mathbf{t}} = 2.4$. The source power is $P_0 = 1000$ and the variance of the measurement noise is selected as $\sigma^2 = 1$. Each UAV quantizes its measurement to 4 bits using uniform quantizers, where the quantization thresholds $[\eta_1, \cdots, \eta_{R-1}]$ are selected to be the values which evenly partition the interval $[-\sigma, \sigma + \sqrt{P_0}]$. We assume that the total bandwidth, i.e., the number of bits that can be transmitted, is $M = 12$ bits. The FC's value per information gain is assumed to be $v_{FC} = 100$. For UAV i, the uncertainty of its cost per unit energy is modeled using a uniform distribution on $[a_i, b_i]$, with $a_i = 5$ and $b_i = 20$. The FC is located at $(6, 6)$, and the parameters in the energy cost function are $\epsilon = 10^{-3}, \phi = 10^{-1}$. $N_s = 5000$ particles are drawn from $p(l_t)$ in order to estimate the location of the target. The result is obtained by averaging over 5000 Monte Carlo trials.

In Fig. 1, we divide the RoI into 25 cells, and plot the utility and mean square error (MSE) of the FC when the total number of UAVs deployed varies and takes values from $N \in \{9, 16, 25, 36, 49, 64\}$. We can see that as the number of UAVs increases, the system performance increases since the FC's utility becomes larger and MSE becomes smaller. This is because the competition among UAVs increases as

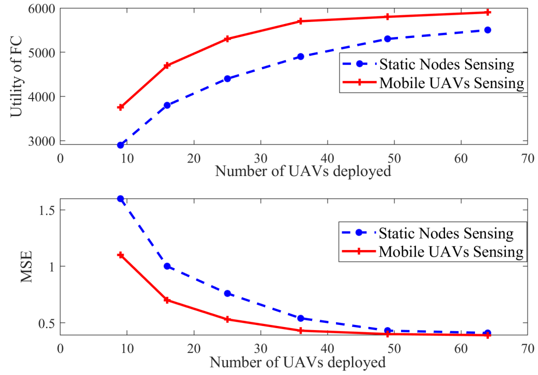

Fig. 1. Utility and MSE of FC when different number of UAVs are deployed.

the number of UAVs becomes larger, in which case the FC has a better chance to select more informative UAVs that require less payments. We can also see that the plots converge when there are a large number of UAVs. This is because perfect competition is reached when the number of competitors is large, which results in saturation of the market. Besides, compared to the scenario where all sensing nodes are static, our proposed mechanism, which allows the mobility of UAVs, clearly improves the system performance.

In Fig. 2, we divide the RoI into different number of cells $J = \{9, 16, 25, 36, 49, 64\}$, and plot the utility and MSE of the FC with respect to the number of cells. The number of UAVs deployed in the RoI takes values from $N \in \{16, 25, 36\}$. We find that the FC has better performance, in terms of larger utility and smaller MSE, as the number of cells in the RoI increases. Since more computations are needed when there are larger number of cells, there is a trade-off between the computation effort and system performance. It can been seen from Fig. 2 that both the FC's utility and the MSE converge as the number of cells increases. The convergence rate is faster when we deploy a larger number of UAVs.

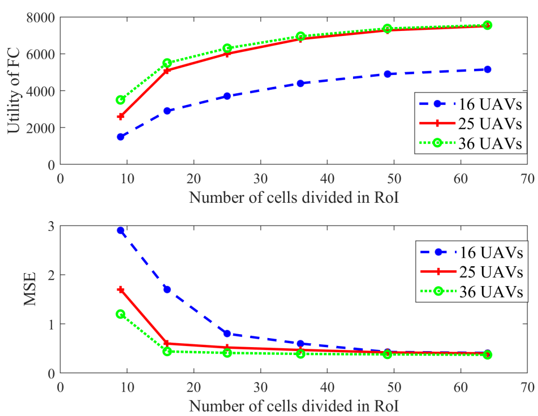

Fig. 2. Utility and MSE of the FC when the RoI is divided into different number of cells.

V. Conclusion

This work explored the UAV selection strategy for target localization in a scenario where UAVs compete to sell information to the FC. To maximize the expected utility for the FC, we designed a reverse auction mechanism and derived the $\boldsymbol{q}$ function that determines which subset of UAVs to select and where they should move to, as well as the $\boldsymbol{p}$ function that represents the payments that should be made to the UAVs. Our mechanism guarantees individual rationality and incentive-compatibility, and at the same time it achieves higher utility and lower MSE than the situation where the sensing nodes are kept static. We also showed that the accuracy of localization improves as we divide the RoI into more cells and deploy a larger number of UAVs. In the future, we will explore the non-myopic UAV movement scheduling in target tracking, where the movements of UAVs are pre-determined to anticipate the trajectory of a mobile target in the next time slot.

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