Movement-Based Incentive for Crowdsourcing

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Abstract—Most research on incentive mechanism design in crowdsourcing has focused on how to allocate sensing tasks to participants to maximize the social welfare. However, none of them consider the coverage holes created by the uneven distribution of participants. As a result, most participants in some popular areas compete for tasks, while many tasks in unpopular areas cannot be completed due to the lack of participants. In this paper, we design a movement-based incentive mechanism for crowdsourcing, where participants are stimulated to move to the unpopular areas and complete the sensing tasks in these areas, which benefits both participants and the platform. We formulate a task allocation problem considering controlled mobility. Since the task allocation problem is NP-hard, we propose a greedy algorithm to solve it, and design a critical payment policy to guarantee that participants declare their cost truthfully. Theoretical analysis shows that our proposed incentive mechanism satisfies the desired properties of truthfulness, individual rationality, platform profitability, and computational efficiency. Evaluation results show that the proposed movement-based incentive mechanism outperforms existing solution under various conditions.

Index Terms—Crowdsourcing, incentive mechanism design, auction theory, mobility control.

I. INTRODUCTION

With the rapid development of smartphones and their embedded sensors, crowdsourcing has been a promising approach to collect and analyze distributed sensed data with the help of smartphone users [1]. A typical crowdsourcing system consists of a platform residing in the cloud and many smartphone users (participants) [2]. Participants act as sensing service providers, and the platform recruits them to provide sensed data. By leveraging crowdsourcing, people have designed new applications to achieve a wide variety of services [3] [4], such as health care [5], environmental monitoring [6], noise pollution monitoring [7], 3D modeling of the urban buildings [8], and radio frequency fingerprinting indoor location [9]. The success of these crowdsensing applications critically depends on the participation of a large number of smartphone users. However, users may not be willing to participate, as participating in a mobile sensing task will incur extra operational costs such as battery and computing power. In addition, users also expose themselves to potential privacy threats by sharing sensed data tagged with location and time. Considering previous problems, incentive mechanisms are needed to encourage the participation of smartphone users. Therefore, incentive mechanisms have attracted a lot of interests from both academia and industry [10], [11].

Some recent works have been devoted to incentive mechanism design in crowdsourcing, using pricing or auction [12]–[14]. Most of these works focus on how to allocate the sensing tasks to participants to maximize the social welfare. However, none of them consider the coverage holes [15] [16] created by the uneven distribution of participants. In practice, most participants are clustered in some popular areas, and many of them may lose in the auction. In contrast, many tasks in the unpopular areas cannot be completed due to the lack of participants.

For example, the 3D modeling of a building in [8] requires complete angular coverage around the building’s perimeter, with several photos taken from different angles. However, in practice, most participants are clustered in the popular areas such as the entrance or exit of the building [17]. To verify this, we crawled Flickr for photos of a library in our area. Fig. 1 shows the location of crawled Flickr photos denoted as stars, and the location of photos required for 3D modeling denoted as circles. As can be seen, the participants tend to be clustered in popular areas although the platform requires photos around the building for 3D modeling. Another example is to build a noise pollution map of a city [7], where the platform requires sensed data all over the city, but there may not be enough participants in some parts of the city.

For many crowdsourcing-based services such as the aforementioned examples, their effectiveness is a direct result of the sensing task coverage [18]. In order to enlarge the sensing task coverage, it is important to motivate the participants in popular areas to move to unpopular areas and complete the sensing tasks in these areas. In reality, there will be some cost (e.g., time, energy, dissatisfaction, etc.) for a user to move from one place to another. Therefore, an incentive is needed to encourage participants to move to the unpopular areas.

In [19], Talasila et al. proposed a sensing game based incentive scheme to attract participants to move to unpopular areas. However, it is limited to gaming, and not for general application. In this paper, we design a general movement-based incentive mechanism for crowdsourcing applications, where...
The main contributions of the paper are as follows.

- To the best of our knowledge, we are the first to design a general movement-based monetary incentive mechanism for crowdsourcing applications, where participants are stimulated to move under the instructions from the platform to benefit both participants and the platform.
- Theoretical analysis shows that the proposed mechanism satisfies the desired properties of truthfulness, individual rationality, platform profitability, and computational efficiency.
  
Evaluation results show that the proposed movement-based incentive mechanism outperforms existing solution under various conditions.

The remainder of our paper is organized as follows. In Section II, we briefly review the related work. Then, we present the system model and the problem formulation in Section III. In Section IV, we propose the movement-based incentive mechanism. Theoretical analysis of the proposed incentive mechanism is presented in Section V. We present the evaluation results in Section VI. Section VII concludes our work.

II. RELATED WORK

There has been lots of research on incentive in crowdsourcing, which can be generally divided into two categories.

One category of existing work encourages participation by nonmonetary incentives, such as the competitive game-based incentive [8], [19], [20] and the reputation-based incentive [21]. However, it is hard to use nonmonetary incentives to motivate participants to collect sensed data.

Another category of existing work motivates participation by monetary incentives. In [13], Lee et al. proposed the virtual participation credit to prevent participants from dropping out of the reverse auction, but they only analyzed the situation that participants applied for one sensing task. In [12], Yang et al. considered two types of incentive mechanisms. They first proposed a Stackelberg game-based incentive mechanism for the platform-centric model, and then proposed a reverse auction-based MSensing incentive mechanism for the user-centric model. The work in [22], [23] investigated online incentive mechanisms for mobile crowdsourced sensing. The work in [14], [24] analyzed incentive mechanisms by considering the location information and coverage constraints. However, they did not consider the mobility of participants.

The work in [25] and [26] discussed user recruitment and task allocation by utilizing the mobility of participants. They relied on predicting participants’ mobility, which may not be accurate. The work in [27] focused on task allocation to satisfy the time budget constraint for each participant by taking into account both the geographical characteristics of sensing tasks and the movement of mobile users. However, users may not follow the instructions of the platform to move without efficient incentive in practice. Moreover, none of them consider controlling the mobility of participants to enlarge the sensing task coverage. In this paper, we proposed movement-based incentive mechanism, where the platform can leverage the movement-based incentive to motivate the participants in popular areas to move to unpopular areas and complete sensing tasks there to achieve enlarged sensing task coverage.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

We consider a crowdsourcing system consisting of a platform residing in the cloud and many participants, as shown in Fig. 2. The platform accepts sensing requests from platform users and devises multiple sensing tasks based on the sensing requests. The platform publishes these sensing tasks to participants periodically. There are \( m \) sensing tasks and the set of sensing tasks is denoted by \( T = \{t_1, t_2, \ldots, t_m\} \). A sensing task \( t_j \) specifies the desired sensing service and
the corresponding location where the sensed data should be collected. Let \((x_j^i, y_j^i)\) denote the location of sensing task \(t_j\) and let \(\nu_j\) denote the value of sensing task \(t_j\) to the platform. Each participant \(i\) is aware of his own location \((x^i_b, y^i_b)\). Each participant \(i\) can only complete the sensing tasks within his sensing range. Let \(r\) represent the sensing range of each participant. Let \(c_i\) denote the cost for participant \(i\) to complete one sensing task within his sensing range.\(^1\) Let \(\psi_i\) denote the capacity of participant \(i\), which is the maximum number of sensing tasks participant \(i\) can complete due to the limited battery power and time budget. Similar to existing work [14], [24], [27], we assume that each participant shares his current location and capacity with the platform.

In order to enlarge the sensing task coverage, the platform motivates participants to move from popular areas to unpopular areas. There will be some cost (e.g., time, energy, dissatisfaction, etc.) for a participant to move from one place to another. We introduce a moving cost function \(g(d)\), which is a monotonically increasing function of moving distance \(d\). The moving cost function is determined by the participant himself (his time, the remaining battery capacity, and various environmental and human factors). Due to the limited time of each participant, we assume that each participant has a upper bound of moving distance [28], [29]. Once the distance to the destination is beyond the upper bound, the participant is not willing to move there. Fig. 3 shows an example of the moving cost function \(g(d)\) of a specific participant \(i\), where \(\delta_i\) is the moving distance upper bound of participant \(i\). The curve represents participant \(i\)'s moving cost as the moving distance increases. For example, the moving costs are \(g_1\) and \(g_2\) with moving distances \(d_1\) and \(d_2\). Similar to [30] and [31], we model the moving cost function as: \(g(d) = e^{\eta d} - 1\), where \(\eta\) determines the scale of \(g(d)\), and a smaller \(\eta\) results in lower moving cost. Participants have different value of \(\eta\) due to the difference of environmental and human factors. In the future, we will consider more practical moving cost functions and study how such cost function affects the incentive mechanism design.

In order to motivate participants to move from one place to another place, the platform should provide movement-based incentive, which is relevant to the moving cost function. We define the movement-based incentive for a specific participant \(i\) as follows:

\[
f_{\eta_i}^c(d_i) = e^{\eta_i d_i} - 1,
\]

where \(\eta_i^c\) is in the critical bid of participant \(i\) described in the Subsection IV-C. Participant \(i\) moves from his current location to his destination following the shortest path calculated based on the map [32]. The moving distance \(d_i\) is the length of the shortest path. In practice, many sensing tasks are time-dependent and have a specified deadline, a participant cannot complete the sensing tasks located far away from each other. Therefore, the platform motivates each participant to move to only one destination and complete sensing tasks there. The notations are listed in Table I.

We use a reverse auction framework to model the interactions between the platform and the participants. The participants act as sellers to send bids, which include the cost \(c_i\) for completing one sensing task and the parameter \(\eta_i\) in moving cost function. The platform then acts as the buyer to allocate sensing tasks to each participant and buy the sensed data from them.

Fig. 2 illustrates the reverse auction between the platform and participants. First, the platform publishes the set of sensing tasks \(T\) to participants. Then, each participant \(i\) announces a bid \(b_i = \{c_i, \eta_i\}\) to apply for sensing tasks. Upon receiving the set of bids from the \(n\) participants, \(B = \{b_1, b_2, \ldots, b_n\}\), the platform allocates sensing tasks to participants and determines payment to each winning participant. Let \(S\) denote the task allocation result, and \(S = \{S_1, S_2, \ldots, S_n\}\) where \(S_i\) is the set of sensing tasks allocated to participant \(i\). \(P = \{p_1, p_2, \ldots, p_n\}\) denotes the payment determination result where \(p_i\) is the remuneration of participant \(i\). If \(i\) wins, \(S_i \neq \emptyset\) and \(p_i \neq 0\). If \(i\) loses, \(S_i = \emptyset\) and \(p_i = 0\). Finally, each winning participant moves to the destination and completes its sensing tasks and sends the sensed data back to the platform. We define the payoff of the platform, the payoff of each participant \(i\), and the social welfare as follows:

**Definition 1.** The payoff of the platform is the total value of sensing tasks completed by participants minus the total

\[\text{Social Welfare} = \sum_{i=1}^{n} \nu_i + \sum_{i=1}^{n} c_i - \sum_{i=1}^{n} p_i.\]
payment to the winning participants,

\[ u_0 = \sum_{b_i \in B} \left( \sum_{t_j \in S_i} \nu_j - p_i \right), \]

where \( \sum_{t_j \in S_i} \nu_j \) is the value of the sensing tasks completed by participant \( i \), and \( p_i \) is the payment to participant \( i \).

**Definition 2.** The payoff of each participant \( i \) is

\[ u_i = p_i - (|S_i| \cdot c_i + f_{\nu_i}(d_i)), \]

where \(|S_i| \cdot c_i\) is the cost for completing the set \( S_i \) of sensing tasks, and \( f_{\nu_i}(d_i) \) is the cost for moving distance \( d_i \).

**Definition 3.** The social welfare is the difference between the total value of completed sensing tasks and the sensing cost,

\[ w = \sum_{b_i \in B} w(i, S_i), \]

where \( w(i, S_i) = \sum_{t_j \in S_i} (\nu_j - c_i) - f_{\nu_i}(d_i) \) is the contribution that participant \( i \) makes to the social welfare by completing the set \( S_i \) of sensing tasks. The social welfare is the sum of all participants’ contributions.

The social welfare is the aggregate of the platform’s payoff and participants’ payoffs, because the payment in the payoff of the platform and the payment in the payoffs of participants cancel each other from a social perspective.

**B. Problem Formulation**

The incentive mechanism consists of two components: task allocation and critical payment determination, which are formulated as follows.

**Definition 4. Task Allocation Problem.** Find the task allocation \( S = \{S_1, S_2, \cdots, S_n\} \) such that

\[ \max \sum_{b_i \in B} \left( \sum_{t_j \in S_i} (\nu_j - c_i) - f_{\nu_i}(d_i) \right) \]

s.t. \( d_i < \delta_i, \ i = 1, \cdots, n \)

\[ |S_i| \leq \psi_i, \ i = 1, \cdots, n. \]

The objective of the task allocation problem is to maximize the social welfare. The first constraint indicates that the platform can motivate participant \( i \) to move distance \( d_i \) \((d_i \leq \delta_i)\). The second constraint shows that participant \( i \) can complete at most \( \psi_i \) sensing tasks.

**Definition 5. Critical Payment Determination Problem.** For each participant \( i \), let \( b_i \) denote the truthful bid and \( \tilde{b}_i \) denote the untruthful bid. \( u_i(b_i) \) and \( u_i(\tilde{b}_i) \) are the payoffs of participant \( i \) by declaring the truthful bid \( b_i \) and the untruthful bid \( \tilde{b}_i \), respectively. The critical payment determination problem is to design a payment determination algorithm such that

\[ u_i(b_i) \geq u_i(\tilde{b}_i). \]

A payment determination algorithm resulting from the critical payment determination problem can guarantee that participants declare their costs truthfully.

Our objective is to design an incentive mechanism that solves the two problems defined above. This mechanism should also satisfy the following four desirable properties:

1. **Truthfulness**: An incentive mechanism is truthful, if and only if the winning participant selection is monotonic and the payment is critical.
2. **Individual Rationality**: The payoff of each participant \( i \) is nonnegative, \( u_i \geq 0, \ i = 1, 2, \cdots, n \).
3. **Platform Profitability**: The payoff of the platform is nonnegative, \( u_0 \geq 0 \).
4. **Computational Efficiency**: The outcome can be solved in polynomial time.

**IV. MOVEMENT-BASED INCENTIVE MECHANISM**

In this section, we propose our movement-based incentive mechanism consisting of the task allocation algorithm and the critical payment determination algorithm. First, we prove that the task allocation problem is NP-hard. Then, a greedy algorithm is proposed to solve the task allocation problem within polynomial time. Finally, a critical payment determination algorithm is proposed, which guarantees that each participant declares his cost truthfully.

**A. Complexity Analysis of Task Allocation Problem**

In this subsection, we prove that the task allocation problem is NP-hard.

**Theorem 1.** The task allocation problem is NP-hard.

**Proof.** First, we simplify the task allocation problem to a special case \( \text{INSTANCE A} \) by assuming that each participant \( i \) has a fixed set \( S_i \) of sensing tasks to complete. Then, we prove \( \text{INSTANCE A} \) is NP-hard by giving a polynomial time reduction from the NP-hard SET COVER problem. Finally, we relax the assumption, and show that the task allocation problem is NP-hard.

 INSTANCE A: A set \( \mathcal{D} = \{D_1, D_2, \cdots, D_n\} \), where \( D_i \) is the set of sensing tasks that participant \( i \) decides to complete. The universe set of sensing tasks is \( U = \bigcup_{D_i \in \mathcal{D}} D_i \), and its size is \( m' \), where \( m' \leq m \). We set the value of each sensing task equal to \( v' \). \( v' \) is a constant, and \( v' \geq 1 \). We assume that the cost for each participant \( i \) to move to his destination and complete the set \( D_i \) of sensing tasks is \(|D_i| \cdot c_i + f_{\nu_i}(d_i) = 1\).

The question is whether there exists a subset \( \mathcal{D}_0 \subseteq \mathcal{D} \) such that \( \sum_{D_i \in \mathcal{D}_0} w \geq v' \cdot m' - k \), where \( w \) is the social welfare, and \( k \) is the size of \( \mathcal{D}_0 \).

 SET COVER: A set \( \mathcal{C} = \{C_1, C_2, \cdots, C_n\} \), where \( C_i \) is the set of some elements in the universe set \( V = \bigcup_{C_i \in \mathcal{C}} C_i \). The question is whether a subset \( \mathcal{C}_0 \subseteq \mathcal{C} \) of size \( k \) exists such that every element in \( V \) belongs to at least one member in \( \mathcal{C}_0 \).

We prove that there is a solution to \( \text{INSTANCE A} \) if and only if there is a solution to the \( \text{SET COVER} \) problem. We first prove the forward direction. Let \( \mathcal{D}_0 \) be a solution to \( \text{SET COVER} \). We prove that there is a solution to \( \text{INSTANCE A} \) if and only if there is a solution to the \( \text{SET COVER} \) problem. We prove the backward direction. Let \( \mathcal{C}_0 \)
Algorithm 1: Task Allocation

**Input:** set of $m$ sensing tasks $T = \{t_1, t_2, \cdots, t_m\}$, set of $n$ bids $B = \{b_1, b_2, \cdots, b_n\}$.  

**Output:** set of winning participants $B_0$, set of task allocation results $S_0$.  

1. $B_0 \leftarrow \emptyset$, $S_0 \leftarrow \emptyset$, $T_0 \leftarrow T$;  
2. **while** $B_0 \neq B$ & $T_0 \neq \emptyset$ **do**  
3. **for all** $b_i \in B \setminus B_0$ **do**  
4. Find the set of sensing tasks $S_{i,B_0}$;  
5. $w(i,S_{i,B_0}) = \sum_{t_j \in S_{i,B_0}} (\nu_j - c_i) - f_{\eta_i} (d_i)$;  
6. **end for**  
7. $i = \arg \max_{b_i \in B \setminus B_0} w(i,S_{i,B_0})$;  
8. **if** $w(i,S_{i,B_0}) \leq 0$ **then**  
9. QUIT  
10. **end if**  
11. $B_0 \leftarrow B_0 \cup \{b_i\}$, $S_0 \leftarrow S_0 \cup \{S_{i,B_0}\}$, $T_0 \leftarrow T \setminus S_0$;  
12. **end while**

be a solution to the SET COVER instance. We can select the corresponding set $D_0$ as the solution to INSTANCE A. Clearly, $w = v' \cdot m' - |D_0| \geq v' \cdot m' - k$.

Now we relax the assumption, i.e., the platform can allocate different set $S_i$ of sensing tasks to each participant $i$. The set $S$ is not fixed, and there are a finite number of possibilities. Each given $S$ is corresponding to the set $D$ in INSTANCE A, and it is NP-hard for the platform to choose a subset $D_0 \subseteq D$ ($S_0 \subseteq S$) such that $w \geq v' \cdot m' - k$. Hence, the task allocation problem in Eq. (5) is also NP-hard.

**B. Task Allocation Algorithm**

To achieve the desired property of computational efficiency, a greedy algorithm is proposed to solve the task allocation problem. The idea is to pick the participant who can make the highest contribution to the social welfare, until the social welfare cannot benefit from the unselected participants.

Let $B_0$ denote the set of bids from the selected winning participants. Let $S_0$ denote the set of task allocation results of these winning participants, $S_0 = \{S_1, S_2, \cdots\}$. Initially, $B_0 = \emptyset$ and $S_0 = \emptyset$. In each iteration, the platform selects the destination and finds the set of sensing tasks for each unselected participant $i$ to maximize his contribution to the social welfare, denoted as set $S_{i,B_0}, S_{i,B_0}$ is a subset of $T_0$, where $T_0 \leftarrow T \setminus S_0$. The contribution that participant $i$ can make to the social welfare is:

$$w(i,S_{i,B_0}) = \sum_{t_j \in S_{i,B_0}} (\nu_j - c_i) - f_{\eta_i} (d_i).$$

Then, the platform selects the participant who can make the highest contribution to the social welfare, until the social welfare cannot benefit from the unselected participants. In each iteration, $B_0$ and $S_0$ are updated, and deleted from the set $B$ of bids and the set $T$ of sensing tasks. The pseudo-code is shown in Algorithm 1.

**An Example:** To further illustrate Algorithm 1, we give an example as shown in Fig. 4. In this example, $T = \{t_1, t_2, t_3, t_4\}$, $\nu_1 = \nu_2 = \nu_3 = \nu_4 = 10$. Sensing tasks $t_1$ and $t_2$ locate in the unpopular area, sensing tasks $t_3$ and $t_4$ locate in the popular area. There are 2 participants clustered in the popular area, and $b_1 = \{3, 0.015\}, b_2 = \{2, 0.01\}, \psi_1 = \psi_2 = 2$. We calculate the distances $d_1 = 23.5$, $d_2 = 105$, $d_3 = 135$, as shown in Fig. 4. Since $S_1$ = $\{t_3, t_4\}$, $w(1,S_1) = (10 - 3 + 10 - 3) - (\exp(23.5 \times 0.015) - 1) = 13.58$, and $S_2$ = $\{t_3, t_4\}, w(2,S_2) = (10 - 2 + 10 - 2) - 0 = 16$, participant 2 is first selected and $B_0 = \{b_2\}$ and $S_0 = \{S_2, S_1\}$. The algorithm terminates here because $B_0 = B$. In addition, we have the social welfare $w = 13.58 + 10.17 = 23.75$.

**C. Critical Payment Determination Algorithm**

The payment determination should guarantee that each participant honestly reports his real cost. We propose the critical payment determination algorithm based on the critical payment.

If participant $i$ wins by declaring a bid $b_i^c$, it is paid an amount of monetary reward. The amount is determined according to a critical bid $b_i^c$, which is determined as follows. If $b_i < b_i^c$, participant $i$ wins; if $b_i > b_i^c$, participant $i$ loses. Participant $i$ loses when it cannot make any contribution to the social welfare, i.e., $w(i,S_{i,B_0}) \leq 0$.

The critical bid of participant $i$ is the bid of the first participant $x$ that makes participant $i$ useless, i.e., when $B_0 = \{b_1, b_2, \cdots, b_{x-1}\}, w(i,S_{i,B_0}) \geq 0$; when $B_0 = \{b_1, b_2, \cdots, b_{x-1}, b_x\}, w(i,S_{i,B_0}) \leq 0$. We assume that each participant is replaceable in order to prevent the monopoly. The basic idea of finding the critical bid of participant $i$ is to delete $b_i$ and greedily select other participants until $w(i,S_{i,B_0}) \leq 0$. Suppose the bid of the first participant $x$ that makes participant $i$ useless is $b_x$. The critical bid of participant $i$ is $b_i^c = b_x$, i.e., $c_i^c = c_x$ and $\eta_i^c = \eta_x$. Then, the critical payment to participant $i$ is

$$p_i^c = |S_i| \cdot c_i^c + f_{\eta_i^c} (d_i),$$

where $S_i$ is the task allocation result of participant $i$ ($S_i \in S_0$), $|S_i| \cdot c_i^c$ is the payment for participant $i$ to complete the set $S_i$ of sensing tasks, and $f_{\eta_i^c} (d_i) = \exp(\mu_i^c \cdot d_i) - 1$ is the payment for participant $i$ to move distance $d_i$. 

![Fig. 4. An example. (There are 2 participants and 4 sensing tasks. r is the sensing range.)](image-url)
Algorithm 2 Critical Payment Determination

Input: set of m sensing tasks $T = \{t_1, t_2, \ldots, t_m\}$, set of n bids $B = \{b_1, b_2, \ldots, b_n\}$, set of winning participants $B_0$, set of task allocation results $S_0$.

Output: critical bid $b_i^c$, critical payment $p_i^c$.

1: $B_1 \leftarrow B \setminus \{b_1\}$, $B_2 \leftarrow \emptyset$, $T_1 \leftarrow T$;
2: while $B_1 \neq \emptyset$ & $T_1 \neq \emptyset$ do
3: \hspace{1em} for all $b_x$ in $B_1$ do
4: \hspace{2em} Find the set of sensing tasks $S_{x,B_2}$;
5: \hspace{2em} $w(x,S_{x,B_2}) = \sum_{j \in S_{x,B_2}} (v_j - c_j) - f_{j_0}(d_i)$;
6: \hspace{1em} end for
7: $x = \text{arg max}_{x \in B_1} w(x,S_{x,B_2})$;
8: $B_1 \leftarrow B_1 \setminus \{b_x\}$, $B_2 \leftarrow B_2 \cup \{b_x\}$, $T_1 \leftarrow T \setminus \{S_{x,B_2}\}$;
9: Find the set of sensing tasks $S_{i,B_2}$;
10: if $w(i,S_{i,B_2}) \geq 0$ then
11: \hspace{1em} CONTINUE;
12: end if
13: if $w(i,S_{i,B_2}) \leq 0$ then
14: \hspace{1em} $b_i^c = b_x$;
15: \hspace{2em} $p_i^c = |S_i| \cdot c_i + f_{i_0}(d_i)$;
16: \hspace{2em} RETURN $b_i^c$, $p_i^c$;
17: end if
18: end if
19: end while

The pseudo-code of the algorithm is shown in Algorithm 2. In Algorithm 2, $B_2$ is the set of bids from the selected winning participants. $S_{x,B_2}$ is the set of sensing tasks that the platform finds for each unselected participant $x$ to maximize his contribution to the social welfare, after $B_2$ has been selected. $S_{i,B_2}$ is the set of sensing tasks that the platform finds for participant $i$ to maximize his contribution to the social welfare, after $B_2$ has been selected.

V. THEORETICAL ANALYSIS

In this section, through theoretical analysis, we demonstrate that the movement-based incentive mechanism satisfies the desired properties of truthfulness, individual rationality, platform profitability, and computational efficiency.

According to the theory about the truthfulness of incentive mechanism in [33], the movement-based incentive mechanism is truthful if and only if it satisfies the following two conditions: 1) The winning participant selection in Algorithm 1 is monotonic. 2) Each winning participant is paid the critical payment. Before showing that the movement-based incentive mechanism satisfies the two conditions, we first define monotonicity and critical bid.

**Definition 6. (Monotonicity):** If participant $i$ wins by declaring a bid $b_i$, it also wins by declaring a bid $b_i'$ ($b_i \leq b_i'$).

**Definition 7. (Critical Bid):** For each participant $i$, there is a critical bid $b_i^c$. If participant $i$ declares a bid $b_i \leq b_i^c$, it must win; if participant $i$ declares a bid $b_i > b_i^c$, it will not win.

Next, we prove the movement-based incentive mechanism is truthful by showing that it satisfies the two conditions.

**Lemma 1.** The winning participant selection in Algorithm 1 is monotonic.

**Proof.** Assume participant $i$ wins in the $q$ th iteration by declaring a bid $b_i$, and the contribution that participant $i$ makes to the social welfare is $w(i,S_{i,B_0}) = \sum_{j \in S_{i,B_0}} (v_j - c_j) - f_{j_0}(d_i)$. Suppose participant $i$ declares another bid $b_i'$ ($b_i \leq b_i'$), then $w(i,S_{i,B_0}) = \sum_{j \in S_{i,B_0}} (v_j - c_j) - f_{j_0}(d_i)$. When $S_{i,B_0} = S_{i,B_0}$, since $b_i \leq b_i'$, $w(i,S_{i,B_0}) \geq w(i,S_{i,B_0})$. We next prove that when $S_{i,B_0} \neq S_{i,B_0}$, $w(i,S_{i,B_0}) \geq w(i,S_{i,B_0})$. According to the rule of task allocation in Algorithm 1, before the $q$ th iteration the set $S_{i,B_0} \cup S_{i,B_0}$ of sensing tasks have not been allocated to participants. Thus, $w(i,S_{i,B_0}) = \max\{w(i,S_{i,B_0}), w(i,S_{i,B_0})\} \geq w(i,S_{i,B_0})$. Based on the rule of winning participant selection in Algorithm 1, $i$ must have won in the $q$ th or earlier iteration by declaring the bid $b_i$. It shows that the winning participant selection in Algorithm 1 is monotonic.

**Lemma 2.** Each winning participant is paid the critical payment.

**Proof.** The critical payment is relevant to the critical bid. Assume the critical bid of participant $i$ is $b_i^c = b_x$, where $b_x$ is the bid of participant $x$ in the $p$ th iteration of Algorithm 2. It is obvious that if participant $i$ declares a bid $b_i \leq b_x$, it would win, since $w(i,S_{x,B_2}) \geq w(x,S_{x,B_2})$. On the contrary, if participant $i$ declares a bid $b_i > b_x$, it would lose. Because $w(i,S_{x,B_2}) < w(x,S_{x,B_2})$, participant $i$ cannot win in the $p$ th iteration, and it cannot win in the following iterations, since $w(i,S_{x,B_2}) < 0$ after the $p$ th iteration. This proves that the output $b_i^c$ of Algorithm 2 is the critical bid of participant $i$, and the output $p_i^c$ of Algorithm 2 is the critical payment to participant $i$.

**Theorem 2.** The movement-based incentive mechanism is truthful.

**Proof.** The winning participant selection in Algorithm 1 is monotonic. The payment to each winning participant is critical. According to [33], the movement-based incentive mechanism is truthful.

**Theorem 3.** The movement-based incentive mechanism satisfies the property of individual rationality.

**Proof.** If participant $i$ loses, $S_i = \emptyset$, $p_i = 0$, and his payoff is 0. If participant $i$ wins by declaring a bid $b_i$, his payoff is $u_i = p_i - |S_i| \cdot c_i - f_{i_0}(d_i)$, where $p_i = p_i^c = |S_i| \cdot c_i + f_{i_0}(d_i)$ is the critical payment to participant $i$. Next, we show that $u_i$ is positive when participant $i$ wins. Since participant $i$ wins, his declared bid must be smaller than his critical bid. Then, for each winning participant $i$ that truthfully reports his real cost, his payoff is $u_i = |S_i| \cdot (c_i - c_i) + f_{i_0}(d_i) - f_{i_0}(d_i) > 0$.

We prove that our mechanism satisfies the property of platform profitability by taking advantage of the submodularity of the platform’s payoff $u_0$. Next, we first define the submodular function.
Definition 8. (Submodular Function) Let \( W \) be a finite set. A function \( f : 2^W \mapsto R \) is submodular if
\[
f(P \cup \{w\}) - f(P) \geq f(Q \cup \{w\}) - f(Q),
\]
for any \( P \subseteq Q \subseteq W \) and \( w \in W \setminus Q \), where \( R \) is the set of reals.

Lemma 3. The payoff \( u_0 \) of the platform and the social welfare \( w \) are submodular.

Proof. By Definition 8, we need to show
\[
u_0(P \cup \{b_i\}) - u_0(P) \geq u_0(Q \cup \{b_i\}) - u_0(Q),
\]
for any \( P \subseteq Q \subseteq B \) and \( b_i \in B \setminus Q \), \( P 
\)

Theorem 4. The movement-based incentive mechanism satisfies the property of platform profitability.

Proof. \( u_0 = \sum_{b_i \in B} \sum_{j \in S_i} v_j - p_i \) is the payoff of the platform, and the platform gains profit \( \sum_{j \in S_i} v_j - p_i \) from each participant \( i \). If participant \( i \) loses, \( \sum_{j \in S_i} v_j - p_i = 0 \). Next, we prove that if participant \( i \) wins \( \sum_{j \in S_i} v_j - p_i \geq 0 \). Since the movement-based incentive mechanism satisfies the property of truthfulness, participant \( i \) will win by declaring the critical bid \( b'_i \). We assume \( b'_i = b_{2x} \), then \( \sum_{j \in S_i} v_j - p'_i \) \( = w(i, S_i, B_{1x}) \geq 0 \), where \( B_2 = \{b_1, b_2, \ldots, b_{2x-1}\} \). According to the monotonicity of winning participant selection, participant \( i \) wins in the \( q \)th or earlier iteration by declaring a bid \( b_i \), \( b_i < b'_i \). Based on the submodularity of the platform’s payoff, \( \sum_{j \in S_i} v_j - p'_i \geq w(i, S_i, B_{1x}) \geq 0 \). Therefore, \( u_0 \geq 0 \), the movement-based incentive mechanism satisfies the property of platform profitability.

Lemma 4. The computation complexity of Algorithm 1 is \( O(n^2m \log m) \).

Proof. Since each winning participant should complete at least one new sensing task, and the while loop finishes when the unselected participants cannot make any contribution to the social welfare, the while loop is run at most \( n \) times. The complexity of the for loop is \( O(n) \). In each iteration of the for loop, the platform finds the set \( S_i, B_{1x} \) of sensing tasks that participant \( i \) makes the highest contribution by completing them with complexity \( O(m \log m) \). Finding the winning participant who can make the highest contribution takes \( O(n \log n) \) times. Hence, the computation complexity of Algorithm 1 is \( O(n^2m \log m) \).

Lemma 5. The computation complexity of Algorithm 2 is \( O(n^2m \log m) \).

Proof. The whole loop is run at most \( n \) times. In each iteration of the while loop, there are three main processes. First, computing \( w(x, S_x, B_2) \) of each participant \( x \) takes \( O(nm \log m) \) times (in line 3-6). Second, finding the participant who can make the highest contribution takes \( O(n \log n) \) times (in line 7). Third, finding the set \( S_i, B_2 \) of sensing tasks that participant \( i \) makes the highest contribution by completing them takes \( O(m \log m) \) times (in line 9). Hence, the computation complexity of Algorithm 2 is \( O(n^2m \log m) \).

Theorem 5. The movement-based incentive mechanism satisfies the property of computational efficiency.

Proof. Algorithm 1 for task allocation has polynomial-time computation complexity. Algorithm 2 for critical payment determination has polynomial-time computation complexity. The movement-based incentive mechanism satisfies the property of computational efficiency.

Theorem 6. Let \( w_{\text{opt}} \) be the optimal value of the social welfare that can be achieved by any \( n' \) participants. Let \( w_{\text{greedy}} \) be the social welfare achieved by the Algorithm 1. Then
\[
w_{\text{greedy}} \geq \left(1 - \frac{1}{e}\right) w_{\text{opt}} \quad (9)
\]

Proof. We assume that \( n' \) is the number of winning participants in Algorithm 1. From Lemma 3, the social welfare is submodular. Based on the analysis of approximations for submodular functions in [34], we have
\[
\frac{w_{\text{opt}} - w_{\text{greedy}}}{w_{\text{opt}}} \leq \left(\frac{n' - 1}{n'}\right)^{n'-1}.
\]

Therefore,
\[
w_{\text{greedy}} \geq \left(1 - \frac{n' - 1}{n'} \right) \left(1 - \frac{1}{e}\right) w_{\text{opt}}.
\]

VI. PERFORMANCE EVALUATIONS

In this section, we evaluate the performance of the proposed movement-based incentive mechanism. Although there are many existing works in this area, none of them consider mobility control and most of them are based on the greedy algorithm. Yang et al. [12] proposed a typical greedy algorithm called MSensing incentive mechanism, where participants bid for the sensing tasks within their sensing range, and the platform greedily selects the participant with maximal social welfare contribution without considering mobility control. In this paper, we mainly compare our mechanism with MSensing.

A. Simulation Setup

In our simulations, we deploy a crowdsourcing application in a square of \( 200m \times 200m \). The whole area is divided into 100 grids, each of which is a square of \( 20m \times 20m \). 400 sensing tasks are uniformly distributed across the whole areas and 300 participants are clustered in the popular areas. We assume that the areas around the middle of the square are popular areas. More specifically, the X-position of each
participant follows normal distribution with mean 100m and standard deviation $\sigma = 10m$, and the Y-position of each participant follows uniform distribution within $[0, 200m]$. The sensing range of each participant is $r = 20m$. The capacity of each participant is $\psi = 2$. We illustrate the simulation model in Fig. 5(a). The value of each sensing task to the platform follows uniform distribution within $[6, 10]$. Participants set their cost of completing one sensing task according to uniform distribution within $[3, 5]$. We assume that the parameter $\eta$ in the moving cost function is $\eta = 0.03$, and the moving distance upper bound is $\delta = 70m$.

The following three metrics are used for evaluating the performance of the incentive mechanisms.

- **Task Completion Ratio**, the ratio of sensing tasks being completed by participants.
- **Participant Winning Ratio**, the ratio of participants winning in auction.
- **Social Welfare**, the difference between the total value of the completed sensing tasks and the total sensing cost.

### B. Simulation Results on Task Allocation

With our simulation setup, 400 sensing tasks are uniformly distributed across 100 grids. As a result, there are 4 sensing tasks in each grid. Fig. 5(b) shows the task allocation result of MSensing. As can be seen, only the sensing tasks in the popular areas are completed (marked as 4/3/2/1 completed sensing tasks) and there is no participant completing the sensing tasks in the unpopular areas (marked as 0 completed sensing tasks). There are 118 completed sensing tasks and 59 winning participants. The task completion ratio and the participant winning ratio are $\frac{118}{400} = 29.5\%$ and $\frac{59}{400} = 19.7\%$, respectively. Fig. 5(c) shows the task allocation result of our movement-based incentive mechanism. As can be seen, more participants win in the auction and more sensing tasks are completed. There are 280 completed sensing tasks and 142 winning participants. The task completion ratio and the participant winning ratio are $70\%$ and $47.3\%$, respectively.

Compared to MSensing, our mechanism achieves better performance in terms of task completion ratio and participant winning ratio. The reason is as follows. Most participants are clustered in the popular areas and many of them may lose in the auction by using MSensing, and many tasks in the unpopular areas cannot be completed due to the lack of participants. The movement-based incentive mechanism motivates the participants to move to the unpopular areas and complete the sensing tasks there. Thus our mechanism performs better.

### C. Performance Comparisons

We conduct extensive simulations in three different scenarios, where the standard deviations of participants’ X-coordinates are set to $\sigma = 10m$, $\sigma = 20m$, and $\sigma = 30m$, respectively. In this subsection, we present the performance comparisons between our mechanism and MSensing under various simulation parameters.
1) Number of Participants: Fig. 6 shows how the number of participant \( n \) affects the performance. Generally speaking, the task completion ratio and social welfare increase when \( n \) increases as shown in Fig. 6(a) and 6(c). This is because more sensing tasks can be completed and higher social welfare can be achieved with more participants.

Our mechanism outperforms MSensing in terms of task completion ratio, participant winning ratio, and social welfare. And the performance improvement is larger when there are more participants. For example, with \( n = 150 \) and \( \sigma = 10 \), compared to MSensing, our mechanism increases the task completion ratio by 100%, the participant winning ratio by 66.6%, and the social welfare by 63%. When \( n = 300 \) and \( \sigma = 10 \), compared to MSensing, our mechanism increases the task completion ratio by 145.4%, the participant winning ratio by 143.3%, and the social welfare by 146.7%. The reason is as follows. In our mechanism, the platform leverages the movement-based incentive to stimulate participants to move to the unpopular areas and complete the sensing tasks in these areas. For MSensing, many of the participants are clustered in the popular areas and will lose in the auction. Thus our incentive mechanism performs better.

The performance improvement of our mechanism is much larger when the concentration of participants is higher. For example, when \( n = 300 \), compared to MSensing, our mechanism can increase the task completion ratio by 146.7% with \( \sigma = 10 \), 45.2% with \( \sigma = 20 \), and 26% with \( \sigma = 30 \), as shown in Fig. 6(a). Similar trend can be seen in Fig. 6(b) and Fig. 6(c). This is because when more participants are clustered in the popular areas, more participants will lose auction in MSensing.

2) Upper Bound of Moving Distance (\( \delta \)): Fig. 7 shows how the moving distance upper bound \( \delta \) affects the performance. As can be seen, when \( \delta \) increases, the performance of our mechanism can be significantly improved compared to MSensing in terms of all three metrics. This is because if \( \delta \) is bigger, the platform can motivate participants to move to wider unpopular areas and complete more sensing tasks. We can also see that the effect of \( \delta \) is more significant when \( \sigma \) is small.

3) Moving Cost: Fig. 8 shows how the parameter \( \eta \) in the moving cost function affects the performance. As can be seen, when \( \eta \) increases, the performance of MSensing remain generally stable and the performance of our mechanism drops. The reason is as follows. With larger \( \eta \), the cost for moving becomes larger. Then, more participants cannot win in the auction as shown in Fig. 8(b) and more sensing tasks cannot be completed as shown in Fig. 8(a). Therefore, the social welfare decreases as shown in Fig. 8(c). As shown in the figures, even in the worst case (\( \eta = 0.04 \)), our mechanism still outperforms MSensing in terms of all three metrics.

Summary of Simulation Results: The simulation results show that the movement-based incentive mechanism outperforms MSensing in terms of task completion ration, participant winning ratio, and social welfare. Both of the platform and the participants can benefit from movement-based incentive. From the platform perspective, it achieves enlarged sensing
task coverage by motivating the participants in the popular areas to move to the unpopular areas. From the participants perspective, more participants win in auction and get remuneration.

VII. CONCLUSION

In this paper, we designed movement-based incentive for crowdsourcing, where participants are stimulated to move under the instructions from the platform so as to benefit both participants and the platform. We formulated a task allocation problem considering controlled mobility, and proposed a greedy algorithm to solve it. We also designed a critical payment policy to guarantee that participants declare their cost truthfully. Theoretical analysis shows that our proposed incentive mechanism satisfies the desired properties of truthfulness, individual rationality, platform profitability, and computational efficiency. Evaluation results show that the proposed movement-based incentive mechanism outperforms existing solution in terms of task completion ration, participant winning ratio, and social welfare.

To the best of our knowledge, we are the first to design the general movement-based monetary incentive for crowdsourcing applications. As the initial work, we do not expect to solve all the problems. In the future, we will consider more practical moving cost functions and study how such cost function affects the incentive mechanism design.

REFERENCES


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