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A Novel Incentive Negotiation Mechanism for Participatory Sensing under Budget Constraints

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***Abstract*—Incentive allocation is an important research issue in participatory sensing as it determines the willingness of participants in joining the sensing campaign. Existing incentive approaches either decide the payments without consulting the participants, or require burdensome negotiation procedures like bid-price auction. In this paper, we propose a novel incentive allocation mechanism, which encourages participation and allocates incentives dynamically to achieve accurate sensing results. The proposed mechanism consists of two major elements. The first is a lightweight incentive negotiation procedure, which dynamically offers incentives to participants in spatio-temporal subregions and collects their responses. The second is the optimization problem for incentive allocation as well as it's solution, which aims at maximizing data quality by capturing the amount and the distribution of data samples. Simulations with real datasets confirmed that the proposed solution can provide dynamic incentive offers according to the estimated value of participants' data contribution to the overall quality of sensing result.**

I. Introduction

Participatory sensing encourages ordinary citizens to collect and share sensing data of their surroundings using their mobile phones [1], [2]. It covers different application domains, such as health care, environmental monitoring, emergency and safety. Example applications include noise [3] and air quality monitoring [4] in urban areas. Participatory sensing can gather widely-spread sensing data from mobile users without deploying large amount of wireless sensors. It reduces the deployment and maintenance costs significantly.

Incentive mechanism is important in engaging mobile users to participate in various sensing campaigns. Considering existing incentive negotiation processes, many of them [5], [6] are following the "Price-Decision-First" approach. In this approach, the rewards of participants are decided before collected data are uploaded. It allows the participants to choose whether or not to accept the incentive offer. In contrast, there is another approach called "Data-Upload-First" [7], [8], in which the sensing data are uploaded before the incentive decisions are made. Fig. 1 shows the difference between the two approaches.

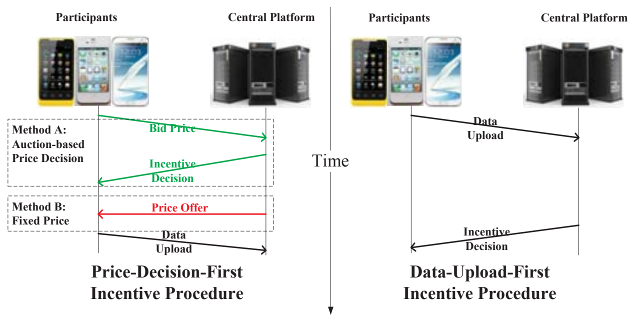

Fig. 1. Two procedures of incentive strategies: Price-Decision-First and Data-Upload-First.

The fairness of the "Data-Upload-First" method is of concern to the participants. The participants may have spent time and energy for collecting and uploading data, but receiving payments less than expected. Thus we believe that the "Price-Decision-First" incentive procedure is more suitable in attracting participants for general participatory sensing systems. However, the current "Price-Decision-First" methods still have considerable drawbacks. For instance, the auction-based negotiation process [7], [9] in the "Price-Decision-First" method causes extra overhead to the resource-constrained mobile devices. Hence, fixed pricing [6] which decides the price offer on each subregion according to the estimated value of the data can be a good alternative in practice, though it is not easy to determine a reasonable price.

In this paper, we propose a lightweight incentive mechanism that allows the platform to provide dynamic price offers to participants according to the availability and spatio-temporal distribution of the supplied data in real-time. Different from the existing auction-based algorithm [6] which pays participant according to their price claims, our incentive mechanism distributes all available budgets in a way that the quality of the overall sensing result is maximized. In particular, we use the price offers in each subregion to model the quantity and spatio-temporal distribution of the sensing data, and formulate the allocation of incentive budget as a multi-objective optimization problem. Then, we propose a greedy algorithm to decide on the price offers within our budget and select participants that can maximize the overall sensing quality.

The main contributions of the paper are as follows:

1) We introduce a dynamic pricing incentive mechanism, which benefits both sides of the data trade. For the participants, their rewards are decided overtly with a simple procedure before their sensing data are uploaded. For the server, the price offers are determined dynamically according to the data's contribution to the overall quality of the sensing results.

2) We estimate the data collection probability in each subregion based on the availability of the participants and their responses to the price offers, and model the amount and spatio-temporal distribution of the collected data mathematically to infer the quality of overall sensing results. Then, we formulate a multi-objective budget constrained optimization problem for incentive allocation and propose a greedy algorithm to maximize the quality of the overall sensing results.

3) We demonstrate the procedure and evaluate the performance of the proposed incentive allocation mechanism by

simulations using real datasets. Compared with the reversed auction approach, our approach has been shown to significantly encourage participants by giving more profits to participants who contribute more to achieve better data quality, and provide better data quality especially when the budget is limited.

The rest of the paper is organized as follows. Section II describes the related work. Section III describes the application scenario and introduces the proposed incentive negotiation procedure. Sections IV and V present the optimization problem of incentive allocation strategy and our novel incentive allocation algorithm. Section VI evaluates the performances by extensive simulations using real datasets. Finally, Section VII concludes this paper.

II. Related work

Different incentive strategies have been investigated for participatory sensing. One main category is the "Price-Decision-First" approach [5], [6]. The "fixed-pricing" method is first adopted, which offers participants a fixed price for their uploaded data. One limitation is that the users do not rely on the server's real-time feedback to take samples, so that some of the samples taken by the users may collect redundant data (e.g., in overlapping area). This will eventually cause extra cost to the task publishers who actually pay for the service.

Lee et al. in [6] first proposed the "auction-based" method, the basic idea of which is that all participants send their expectations and other relevant information, such as locations and sensing capabilities (e.g., ranges), to the platform, and the platform then compares all participants' requirements and chooses some auction winners to purchase their data from. The auction-based incentive method can effectively reduce the sensing cost of the platform and improve the quality of sensing results. Thus, it is becoming the most widely adopted method in the "Price-Decision-First" incentive procedure.

One major drawback of the auction-based method is it causes extra overhead to participants in the incentive negotiation procedure. The platform needs to gather all participants' bid prices to decide which participant to select, so it can not give real-time feedback to each participant regarding his/her bid price. When the server finally makes the decision and informs the auction winner to start data collection, he may have already left the targeting region. Thus, all participants need to collect sensory data even though most of them will not get paid.

Another main category of incentive strategies [8] is based on the "Data-Upload-First" approach. In this approach, the participants are not aware of how much incentives they will receive by the time they upload the sensing data. Nevertheless, one major drawback of the "Data-Upload-First" approach is the uncertainty for the participants to get reasonable rewards. This may discourage participants from contributing data to the platform potentially.

Although the participants may favour the "Price-Decision-First" strategies, the auction-based procedure causes extra overhead to the resource-constrained mobile devices. On the other hand, fixed pricing can be a good alternative in practice, but it is not easy to determine a reasonable price that is beneficial for both the participants and the platform. In this paper, we introduce an extension for the fixed price method based on dynamic pricing according to the availability of participants and the quality of sensing result.

TABLE I
LIST OF NOTATIONS

Notation	Explanation
$\mathcal{S}$	the spatial division of subregions
$\mathcal{T}$	the temporal division of subregion
$\mathcal{R}$	a set of subregions
$\mathcal{O}$	the incentive budget offer, with o_r for each subregion
B	budget constraint
$\mathcal{M}$	the set of participants
n_r	the predicted number of participants in subregion r
$d(o)$	an arbitrary participant's response to incentive o
k, τ	exponent of $d(o)$ by curve fitting
$p_r(o_r)$	data collection probability of subregion r
$\alpha(\mathcal{O})$	amount of possible samplings achieved by $\mathcal{O}$
$\beta(\mathcal{O})$	distribution possible samplings achieved by $\mathcal{O}$
θ_x	the efficiency of allocating a unit of budget to subregion x

III. The Proposed Incentive Negotiation Procedure

A. System Model

A typical participatory sensing system for environmental data collection is shown in Fig. 2. It consists of a sensing task in a targeted region, a central server and a set of mobile users walking freely in the region. As is mentioned earlier, the entire sensing field is divided into a set $\mathcal{S} = \{s = 1, 2, ..., S\}$ of subregions, and the lasting time of a sensing task is also divided into smaller time slots denoted by $\mathcal{T} = \{t = 1, 2, ..., T\}$. The granularity of s and t are determined by the requirement of the task publisher and are given in prior. We represent the subregions in the spatial-temporal domain with $\mathcal{R} = \{\mathcal{R}_1, \mathcal{R}_2, ..., \mathcal{R}_T\}$, where $\mathcal{R}_t = \{R_1^t, R_2^t, ..., R_S^t\}$. Let $\mathcal{M}$ denote the participants inside the sensing region. The symbols used in this paper are summarized in Table.I.

We measure the average error of the sensing results, ε, by comparing the sensing data with the ground truth in all the subregions $\mathcal{R}$. We use $\mathcal{X} \subset \mathcal{R}$ to denote the subregions that have samples. The sensing result in subregions without data samples will be interpolated from the data collected in $\mathcal{X}$. The cause of errors can come from two causes: 1) the interpolated data on subregions $\mathcal{R} \setminus \mathcal{X}$ may be different with the ground truth; 2) some of the collected data on subregions $\mathcal{X}$ are inaccurate. For the sake of simplicity, in this paper we assume that all the participants are contributing trustworthy data.

B. Overview of the Proposed Incentive Mechanism

We proposed a dynamic pricing incentive mechanism for participatory sensing in this work. The mechanism runs iteratively in each time slot t, where $\forall t \in \mathcal{T}$. The central server first calculates the price offer for each subregion. Then, the central server negotiates with the participants in the following steps as shown in Fig. 3.

- First, at the beginning of a time slot t, the server broadcasts through cellular towers to inform all participants in each subregion its sensing requirement in terms of the sensing types, required sensing area and sensing period, and price offer $\mathcal{O}_t = \{o_r | \forall r \in \mathcal{R}_t\}$.
- Second, all participants in each subregion r send the central server their positive or negative responses to the price offer o_r. When a first positive response arrives at the central server, the server notify the participant that he is selected, and informs all other candidate participants. If there are more than one positive responses arrives

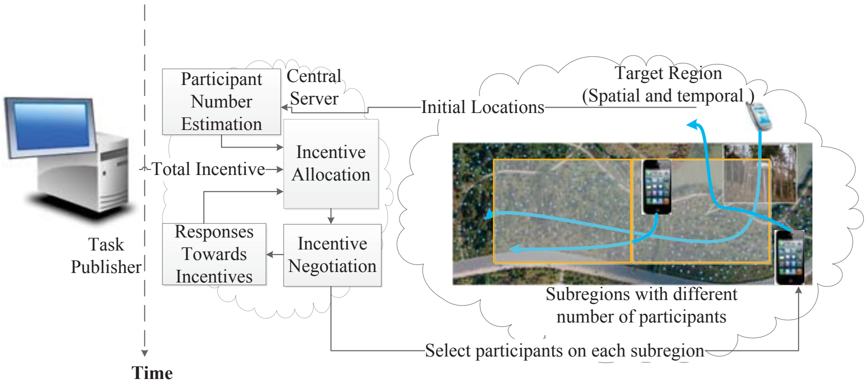

Fig. 2. The considered participatory sensing scenario showing that the entire targeting area is divided into many subregions according to environmental data requirement of task publisher. A subset of participants in different subregions are selected to carry out the sensing tasks.

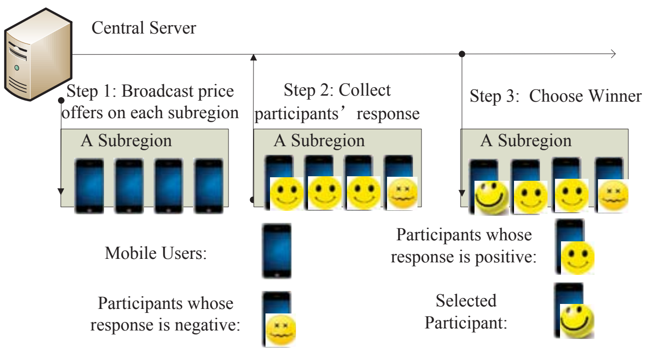

Fig. 3. Procedure of the proposed incentive negotiation mechanism.

, the server randomly selects a participant from the positive candidates and notify him. Otherwise, if all the responses are negative, the incentive of the subregion will be accumulated to the next time slot $t+1$.

- Third, at the end of time slot t, the selected participant in each subregion $\{\forall r \in \mathcal{R}_t\}$ reports his data and gets paid with $\mathcal{O}_t = \{o_r | \forall r \in \mathcal{R}_t\}$. In this work, we consider the mobile users are trustworthy, which means that no participant is malicious or providing incorrect data. The sensor readings provided by the selected participants are supposed to be close to the ground truth. In spite of that, the proposed negotiation mechanism functions well with participants who may provide data with low quality or incorrect readings. To handle the situation, the server will select participants according to their reputations based on previous experiences.

IV. Incentive Allocation

In this section, we will demonstrate how to allocate incentive budgets in a way that the expected amount and distribution of collected data can provide overall interpolated sensing results of best accuracy. The basic idea behind our incentive allocation is the market economy law of supply and demand. Specifically, supply can be the number of available participants in a specific region, and average acceptable price of all users; and demand can be explained as the expected gain by collecting data in an area to the overall sensing quality.

In particular, the supply is how much incentive the participants in each subregions request for data collection. We introduce $\mathcal{P} = \{p_r | \forall r \in \mathcal{R}\}$, $\mathcal{O} = \{o_r | \forall r \in \mathcal{R}\}$ to represent the probability of data collection and the price offer in each subregion. Intuitively, how to allocate the overall budgets among subregions decides the data collection possibility of each subregion. The demand is how important the task publisher expect the data collected in each subregion is to the improvement of overall sensing accuracy. As revealed in our prior work [2], the overall sensing accuracy can be predicted by the amount and distribution of data collection, or say, the set of $\mathcal{P}$.

A. Calculating $\mathcal{P}$

We use $d(o)$ to denote the probability that an arbitrary participant is willing to response positively to a given incentive offer o for data collection. This probability can be obtained based on the previous responses of the participants, or it can be updated in real-time according to the participants' responses to different price offer.

As an example, we conduct an online survey on the Internet with a group of mobile users. We asked them a question "Will you be willing to gather noise level using your mobile phone and upload the collected data given an incentive of (0, 0.1, 0.2, 0.3, ..., 9.5) RMB?". Fifty volunteers returned the questionnaires. For each price offer o, $d(o)$ is calculated by the percentage of participants who are willing to participate in data collection. With curve fitting, we obtain the following function with $k = 0.042, \tau = 0.172$,

$$d(o) \triangleq k o^{\tau}, \tag{1}$$

where k, τ are constants depending on participants' willingness to participate in data collection.

Given a incentive offer o_r, the probability that an arbitrary participant will not accept o_r can be denoted by $1-d(o_r)$. For a subregion r with n_r participants, the probability that none of the participants will accept the offer is $\big(1-d(o_r)\big)^{n_r}$. Thus the probability p_r of having at least one participant in subregion r who will accept the price offer o_r can be calculated by

$$p_r(o_r) = 1 - \big(1 - d(o_r)\big)^{n_r}, \forall r \in \mathcal{R}. \tag{2}$$

To estimate the number of participants n_r in each subregion, the probabilistic Markov model proposed in [10] is adopted. Given the initial locations of participants inside the sensing region $\mathcal{S}$ and the historical trajectories of all participants, the number of participants in each subregion can be estimated.

B. Towards maximal accuracy

As revealed in our prior work [2], the expected accuracy is related with the amount and distribution of data samples. Here we consider the amount and the distribution of data samples under different incentive distribution $\mathcal{O}$, denoted by $\alpha(\mathcal{O})$ and $\beta(\mathcal{O})$, respectively. The predicted amount of samples, $\alpha(\mathcal{O})$, can be calculated by

$$\alpha(\mathcal{O}) = \sum_{\forall r \in \mathcal{R}} p_r(o_r). \tag{3}$$

The distribution of samples, $\beta(\mathcal{O})$, indicates how uniformly the samplings are distributed in the sensing field. In our case, the entire sensing field is divided into a set of areas, $\mathcal{A} = \{a = 1, 2, ...A\}$, where $\bigcup_{\forall r \in \mathcal{A}} r = \mathcal{R}$. The size of an area $a \in \mathcal{A}$ is set to be larger than a subregion r but smaller than the entire sensing field $\mathcal{R}$. We adopt the following weighted-entropy method to evaluate the distribution of data samples, with $\rho_a(\mathcal{O})$ denoting the probability of an arbitrary sample fallen into an area $a \in \mathcal{A}$. We use w_a to denote the weight of each area indicating how tremendously the historical environmental data change in area a. The distribution of data samples can be obtained by

$$\beta(\mathcal{O}) = -\sum_{a \in \mathcal{A}} w_a \rho_a(\mathcal{O}) \log \rho_a(\mathcal{O}). \tag{4}$$

The expected number of samples in area a can be calculated by $\sum_{\forall r \in a} p_r(o_r)$. Then, the ratio $\rho_a(\mathcal{O})$ between the expected number of samples in a and in $\mathcal{R}$, is computed by

$$\rho_a(\mathcal{O}) = \frac{\sum_{\forall r \in a} p_r(o_r)}{\sum_{\forall r \in R} p_r(o_r)}, \forall a \in \mathcal{A}. \tag{5}$$

Based on Eq. (4) and Eq. (5), we have:

$$\begin{aligned} \beta(\mathcal{O}) &= -\sum_{a \in \mathcal{A}} w_a \rho_a(\mathcal{O}) \log \rho_a(\mathcal{O}) \\ &= -\sum_{a \in \mathcal{A}} w_a \frac{\sum_{\forall r \in a} p_r(o_r)}{\sum_{\forall r \in R} p_r(o_r)} \log \frac{\sum_{\forall r \in a} p_r(o_r)}{\sum_{\forall r \in R} p_r(o_r)}. \end{aligned} \tag{6}$$

We formulate a multi-objective optimization problem to maximize both the amount and the distribution uniformity of the collected data. The larger amount of samples and the more even distribution of them will reduce the average error of the sensing results.

$$\begin{aligned} &\max(\alpha(\mathcal{O}), \beta(\mathcal{O})) \\ &\text{subject to:} \quad \sum_{\forall r \in \mathcal{R}} o_r \le B. \end{aligned} \tag{7}$$

Apparently, Eq. (7) is a multi-objective optimization (MOO) problem, where optimal solution may not exist. A simple but efficient problem transformation for MOO problems is the weighted sum method [11]. Using the weighted sum method to solve the problem in Eq. (7) entails selecting scalar weights λ and $1 - \lambda$ for $\alpha(\mathcal{O})$ and $\beta(\mathcal{O})$ respectively and minimizing the following composite objective function of the incentive distribution $\mathcal{O}$, as shown in Eq. (8).

$$\begin{aligned} &\mathcal{O}^* = \{o_r | \forall r \in \mathcal{R}\}^* = \arg\max_{o} \Big(\lambda\alpha(\mathcal{O}) + (1-\lambda)\beta(\mathcal{O})\Big) \\ &\text{subject to:} \quad \sum_{\forall r \in \mathcal{R}} o_r \le B. \end{aligned} \tag{8}$$

C. The Proposed Incentive Allocation Algorithm

We propose an incentive strategy to find the optimum budget offer in each subregion, o_r, where $\forall r \in \mathcal{R}$. The algorithm runs at the beginning of entire sensing period, and iteratively allocate each unit of incentive budget to a subregion that can provide the best gain of the optimization objective in Eq. (8). The proposed algorithm is given in pseudo code (see Algorithm 1) and the detailed descriptions are provided below.

Step 1: Initialization At the beginning of entire sensing time period, the remaining budget B' is set to B. The initial budgets o_r assigned to each subregions $r \in \mathcal{R}_t, \forall t \ge t_0$ are set to 0.

Step 2: Unit Budget Assignment The basic idea behind our algorithm is to iteratively allocate each unit of remaining budget to the subregion that can provide the greatest increase in the objective function Eq. (8). Let $\mathcal{O}$ denote the incentive allocation of the former iteration step. Let $\mathcal{O}'_x$ denote the incentive allocation when the incentive budget of this step is assigned to a subregion r_x. Thus, we have

$$o'_r = \begin{cases} o_r, & \text{if } r \ne r_x \\ o_r + 1, & \text{if } r = r_x \end{cases} \tag{9}$$

Let θ_x be the efficiency metric measuring the increase of the objective function by assigning the budget to r_x. In particular, θ_x can be calculated by the value of the optimization objective given the incentive allocation $\mathcal{O}'_x$ subtracting the value of the optimization objective given the former incentive allocation $\mathcal{O}$, as shown in Eq. (10). Given the initial budget assignments $\{o_r | \forall r \in \mathcal{R}_t, \forall t \ge t_0\}$, the efficiency metric θ_x shows the increase of the objective function with a unit of incentive budget being assigned to a subregion $r_x \in a_x \subset \mathcal{R}_t, \forall t \ge t_0$.

$$\theta_x = \Big(\lambda\alpha(\mathcal{O}'_x) + (1-\lambda)\beta(\mathcal{O}'_x)\Big) - \Big(\lambda\alpha(\mathcal{O}) + (1-\lambda)\beta(\mathcal{O})\Big) \tag{10}$$

Let $\theta_{x_{max}} = \max\{\theta_x | \forall x \in \mathcal{R}_t, \forall t \ge t_0\}$ be the maximum efficiency metric among the subregions. The budget of the current iteration is assigned to the subregion $r_{x_{max}}$ which can provide the maximum efficiency metric $\theta_{x_{max}}$.

Before the incentive allocation phase of this round of iteration, the predicted budget consumption in this subregion can be calculated as $o_x \times p_x(o_x)$. After the incentive allocation, the predicted budget consumption in this subregion is updated as $(o_x+1) \times p_x(o_x+1)$. Thus, the remaining budget is updated accordingly with $B' = B' - (o_x+1) \times p_x(o_x+1) + o_x \times p_x(o_x)$.

The output of each iteration step is a new incentive allocation vector, as calculated by:

$$\mathcal{O} = \{o_r | \forall r \in \mathcal{R}_t, \forall t \ge t_0\}, o_r = \begin{cases} o_r, & \text{if } r \ne r_{x_{max}} \\ o_r + 1, & \text{if } r = r_{x_{max}} \end{cases} \tag{11}$$

Step 3: Looping Repeat step *2* until the remaining budget B' equals to or is less than 0.

Algorithm 1 The proposed incentive allocation mechanism

Require:

time slot t_0; incentive budget B; Subregions $\mathcal{R}$;
Areas and their weight $\mathcal{A}, w_a, \forall a \in \mathcal{A}$;
Estimited number of participants on each subregion $n_r, \forall r \in \mathcal{R}$;
the exponent of o affect the willingness to participate k, τ

Ensure:

Budget Assignments $\mathcal{O}^*$;

$B' \leftarrow B$
$o_r \leftarrow 0, \forall r \in \mathcal{R}_t, \forall t \geq t_0$
while $B' > 0$ **do**
  $\texttt{flag} \leftarrow 0$
  $\texttt{selected\_id} \leftarrow 0$
  $\texttt{max\_eff} \leftarrow 0$
  for subregions $r_x \in a_x \subset \mathcal{R}_t, \forall t \geq t_0$ **do**
    compute r_x's efficiency θ_x in (10)
    if $\theta_x > \texttt{max\_eff}$ **then**
      $\texttt{selected\_id} \leftarrow x$
      $\texttt{max\_eff} \leftarrow \theta_x$
      $\texttt{flag} \leftarrow 1$
    end if
  end for
  if $\texttt{flag} = 0$ or $\texttt{selected\_id} = 0$ **then**
    break
  end if
  $o_{\texttt{selected\_id}} \leftarrow o_{\texttt{selected\_id}} + 1$
  $B' \leftarrow B' - (o_x + 1) \times p_x(o_x + 1) + o_x \times p_x(o_x)$
end while
Return: final vector of budget allocation $\mathcal{O}^* = \{o_r | \forall r \in \mathcal{R}_t, \forall t \geq t_0\}$.

V. Performance Evaluation

A. Simulation Setup

We evaluate the proposed incentive negotiation scheme using the following datasets:

- The GeoLife dataset [12] from Microsoft Research Asia includes real mobility traces of citizens that are used to imitate mobile users in our experiment.
- The GreenOrbs dataset [13] provides sensory readings collected by large-scale sensor network, which are used to simulate environmental data in our experiment.

We performed two online surveys to compare participants' responses to our proposed / the reversed auction based incentive negotiation methods. Two groups of volunteers were randomly selected to answer online questions, as a replacement of their responses to the incentive negotiation procedures implemented on mobile APPs. The 150 volunteers in the first group were asked to answer several yes-no questions about whether they would accept a set of given price offers to participate. The other 50 volunteers in the second group were asked to claim their minimal incentive requests. It is interesting to observe that the answers of the two groups are quite different. As shown in Fig. 4, the bid prices of volunteers from the second group (the "RA" group) is obviously higher than the minimal acceptable prices of the first group (our proposed method). Such result suggests that reducing the complexity of incentive negotiation may encourage participants to ask for lower incentive requirements.

We conduct our experiment in a $200m \times 500m$ region of high movement density from the GeoLife dataset. We use the illumination intensity sensor readings collected on Aug 3rd, 2011 as ground truth. To overlap the trajectories and the sensor readings, the rectangle covered by the sensors was scaled to a $200m \times 500m$ region. The entire region is divided into 8×20 areas of $25m \times 25m$, i.e., $\mathcal{S} = 160$, and the lasting time of 24 hours is divided into $\mathcal{T} = 48$ smaller time slots, each lasting

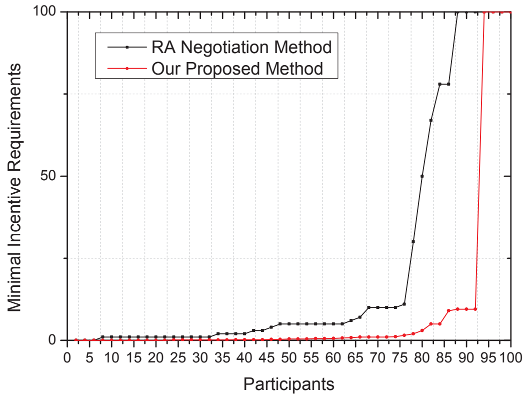

Fig. 4. Responses of online questionnaires

half an hour. An average value of all the sensor readings in each of the $|\mathcal{R}| = 7680$ subregions is taken as the ground truth. The entire region is divided into 120 areas, e.g., $\mathcal{A} = 120$, with each area covering $4 \times 4 \times 4$ neighbouring subregions. To prove the generality of the proposed algorithm, we simply set $w_a = 1, \forall a \in \mathcal{A}$. Besides, we set $\lambda = 0.5$, so that the weights of the amount and the distribution of data collection are equal. We randomly select 150 trajectories from the available trajectories to simulate the movement of participants, i.e., $|\mathcal{M}| = 150$. Both the lowest acceptable price offer and the bid price of each participant are randomly allocated according to the answers in the two online questionnaires.

To compare the system performance of our proposed algorithm, the reversed auction incentive mechanism, referred as RA, is also implemented. The basic idea [6] of "RA" is to iteratively select participants who can provide the highest sensing capabilities with a unit incentive request until the budget runs out.

B. Results

We first show the running process of our proposed approach when the incentive budget $B = 1000$. In each iteration, the efficiency metrics of all subregions are calculated, and the subregion with the highest efficiency is selected and one unit of incentive is allocated to it. Fig. 5 shows the number of participants in the selected subregion in each iteration, and we observe that when limited incentive budgets are given, or say, the value of the overall data collection is low, incentives are mainly allocated to subregions that are most efficient in improving the overall data quality, which either have more participants or provide better increase to the data distribution. When adequate incentive budgets are given, or say, the value of the overall data collection is high, our algorithm gives higher price offers to subregions with few participants which provide non-ignorable details to data interpolation, and gives lower price offers to subregions with more participants where the value of data collection is relatively low due to the sufficient supply of participants.

Next, we evaluate the data accuracy from the collected data after interpolation. Fig. 6 shows the average error of data collection varying the total budget. When the incentive budget is inadequate, our proposed method improves the sensing quality by reducing the average error with 11.3% compared with the RA approach. When the total budget reaches 100000

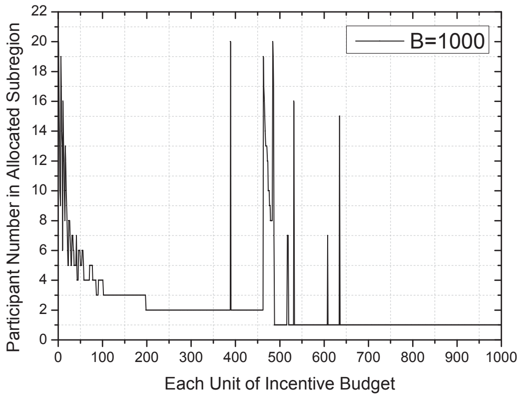

Fig. 5. Number of participants in the selected subregion in each iteration of incentive allocation

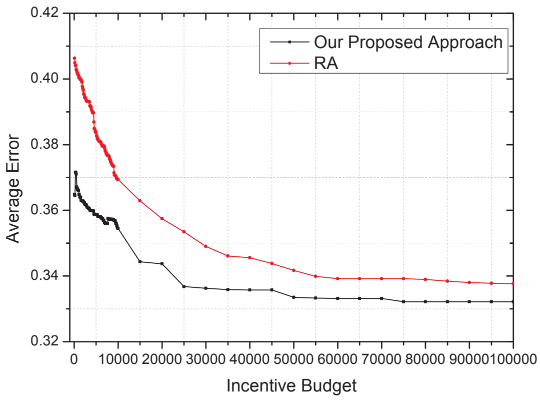

Fig. 6. The impact of total budget on the average error in data collection.

units, the average error of the "RA" method is still 0.5% more than our method. However, to achieve such accuracy, the "RA" method need to recruit 16.1% more participants. This is because we consider not only the amount of data but also the distribution of data.

We compare the average profits of participants with various incentive requirements of the two methods, as shown in Fig. 7. We observe that in our method, participants with lower bid prices are selected more, and get higher average profits. On the contrary, in the "RA" method, participants with bid price equal to 1 contribute a lot, but get no profit. The result further proves that compared with RA, our proposed algorithm can distribute incentive more fairly among participants according to their contribution, and thus can increase participants' willingness to participate.

VI. Conclusion and Future Work

In this paper, we proposed a novel and cost-effective incentive allocation mechanism to foster participants' willingness on sensing and achieve more accurate data in participatory sensing. Different from existing fixed price method, our approach distributes the available budget among the subregions aiming at maximizing the quality of the overall sensing result. Simulations using real-datasets showed that our proposed incentive mechanism enables cost-effective data collection by distributing incentive fairly among the participants according to their data contribution.

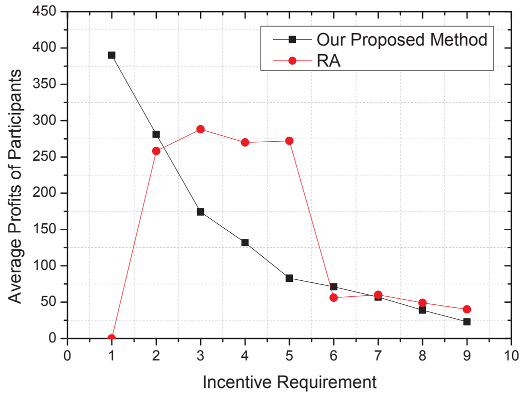

Fig. 7. Average profits of participants with different incentive requirements.

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