A Cross-Space, Multi-Interaction-based Dynamic Incentive Mechanism for Mobile Crowd Sensing

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***Abstract*—With the surge of varied crowd sensing systems, active user participation becomes a crucial factor that determines whether a crowd sensing system can provide good service quality. To encourage user participation in mobile crowd sensing, we propose a novel incentive mechanism called CSII—a Cross-Space, multi-Interaction-based Incentive mechanism. CSII can estimate the value of a task based on the sensing context and historical data. It then has multiple interactions with both the task requester and the candidate contributors to provide a suggestion on budget and select suitable people to form the worker group. Finally, the requester pays the workers' reward that they deserved by reverse auction based on their reputation and bids. Both online and offline data are leveraged to estimate task value and user quality for a particular task. Experiments show that the incentive mechanism can achieve good performance in terms of acceptance ratio, overpayment ratio, user utility, and so on.**

Keywords—Incentive Mechanism; Cross-Space; Multi-Interaction; Mobile Crowd Sensing; Smartphones

I. INTRODUCTION

Mobile Crowd Sensing (MCS) systems rely on a large amount of participants with smartphones to sense data of interest and share it through backend servers [1]. The collaboration of numerous participants on task assignment and data collection makes a great difference in accomplishing large-scale sensing tasks, such as traffic monitoring [2, 3] and environment monitoring [4, 5]. In MCS systems, whether there are adequate users to participate has critical impact on the workability and quality of such systems. However, there are several problems that may hinder user participation. First, the usage of smartphone sensors brings human concern on privacy leakage. Second, the participants need to transmit the sensed data to a server, which can raise cost on network traffic. Finally, the consumption of computation/energy resources would also reduce user willingness on participation. To overcome these problems, incentive mechanisms are crucial to simulate user participation in MCS systems.

A lot of work has been done on the incentive mechanisms [6-14] for MCS systems. However, they do not fully consider the characteristics of MCS. First, MCS refers to human behaviors in both cyber and physical spaces [1], while existing works mainly focus on the data and information from the physical world. As presented in [15], to better understand and provide support to human behaviors, we should leverage cross-space, multi-sourced data. For example, the spatio-temporal characters of human can be better depicted when using heterogeneous data sources. Second, existing work pays little attention to the interaction among task providers, the backend sever, and participants, which may impact the quality of MCS task completion. For instance, without prior knowledge about the dynamics of an area, it is often difficult for the task requester to raise a well-planned budget to execute a MCS task within that area. This, however, can be enhanced by the interaction between the task provider and the backend server (the server has rich history information and aggregated knowledge about the city).

Given the above issues, we propose a novel MCS incentive mechanism called CSII − a Cross-Space multi-Interaction-based dynamic Incentive mechanism. The main contributions of our work are summarized below:

- It leverages cross-space data (online and offline) to better characterize the sensing tasks and stakeholders: to estimate the value of a task (for budget suggestion), and to select suitable participants to perform the sensing task.
- Interactions among the stakeholders in MCS systems are considered to improve the quality of sensed data. The interactions are integrated in different task performing stages, which facilitates dynamic budgeting/pricing and improves the quality of user contributed data.

Experiments over a combination of online crawled data and task simulation indicate that the CSII mechanism is effective to motivate user participation and can provide high quality of sensed data.

II. RELATED WORK

Researches on MCS incentive mechanisms can be broadly categorized into two modes: online and offline.

In the online incentive mode, participants arrive one by one in a random order and the platform has to decide whether a task should be assigned to a participant upon her arrival based solely on the information of previous participants who arrive earlier than the current one. In work [6-9] a certain number of participants who arrival at the beginning are rejected to perform the sensing task and their informations are used as samples to learn a threshold, which acts as a criterion on task assigment to other participants arriving later. However, this solution cannot guarantee the same winning chance for everybody, because the first batch of participants who are selected to train the threshold have no chance to win no matter how low their bids are. In other words, the participants arriving early have no rewards to report their bids, which may delay the completion time of the task and even result in task starvation[7].

In the offline incentive mode, the backend server has the whole information about the data contributors, including bids, sensing costs, and so on. [10-14] are typical examples, where well-suited participants are selected for data collection and the reverse auction method is used. All these studies assumed a static budget for any published task, the dynamics of tasks in terms of spatio-temporal contexts are not considered. Though [13, 14] proposed an incentive mechanism that selects a representative subset of the participants according to their location with a constrainted budget, it does not allow task difficulity evaluation and dynamic budgeting.

Different from existing incentive mechanisms, to make full use of the spatio-temporal contexts and crowd interactions, we propose a cross-space, multi-interaction-based dynamic incentive mechanism (CSII) for MCS systems. The incentive mechanism will be optimized with the interactions among task providers, participants, and the platform or server. Cross-space data mining and sensing task value estimation will be used for task evaluation and participant selection.

III. SYSTEM ARCHITECTURE AND ANALYSIS

To motivate people participating in MCS systems, two contributions are made in the CSII mechanism: interactions among the entities with spatio-temporal contexts in MCS systems and cross-sapce data for characterizing the sensing tasks and stakeholders. We present the architecture as well as the main characters of CSII in detail below.

A. *The CSII Architecture*

In the CSII mechanism, a sensing task is characterized by a quadruple T=<m, o, s, d>, where m is the requester's expected number of workers to perform the task; For the convenience of task publishment, we devide a district (e.g., a city in physical space) to a grid, and each cell within the grid is called a square region in our study. In the task T, o is a square region where data shoule be collected; s is the start time to perform the task; d is the deadline, before which the sensed data must be submitted. Here we define that the square o is a continuous region. The time during the start time and the deadline is called valid period for a particular sensing task. We define that the sensing task refered in our study is atomic [14], and complex tasks can be considered as combinations of atomic tasks. For example, a complex task that requires to collect data in several discontinuous square regions can be devided into atomic tasks of each square region.

Three interaction entities are included in the CSII mechanism to perform a MCS task: requesters or task publishers, the task management platform (i.e., the backend server, 'platform' in short), and workers. A requester is the one who publishes sensing tasks on the task management platform. Workers are the ones who perform sensing tasks with incentive mechanisms. The task management platform is responsible for worker selection and bargain/payment mediation among the requester and workers. Four stages are involved to motivate user participation in MCS systems: *task publishment*, *task assignment*, *winner selection*, and *payment mediation*. The architecture of the CSII mechanism is illustrated in Fig. 1, which contains multiple interactions among the three entities (explained in the next subsection) and the usage of cross-space (online/offline) data. The working procedure and the collaboration among different modules of CSII are presented below.

A requester firstly publishes a sensing task on the platform. Before assigning the task to the potential workers, the platform estimates the value of the sensing task based on the LBSN (Location-based Social Network, e.g., Foursquare and Jiepang) online data and suggests a budget to the requester. In the interaction of this stage, the requester can adjust his budget based on the suggested task value. Afterwards, the platform will select workers to perform the task. An important thing to be considered is the matching between the requested sensing context and user behavior patterns, i.e., to estimate whether a user is likely to meet the requested sensing context. In the current study, we mainly consider about the spatio-temporal behavior pattern of users, which is learned from LBSN data. The workers then decide whether to accept the task assigned to them. Afterwards, the selected workers will perform the task and send their claimed bid price to the platform. The platform selects the winner by reverse auction. In order to reduce the cost on data transmission, only the winner submits the sensed data to the requester. To enhance the willingness of user participation, both the winner and losers are paid based on an improved payment stragety.

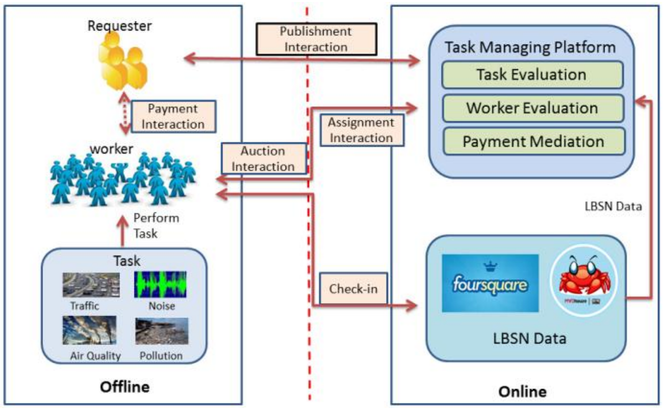


Fig.1. The architecture of the CSII mechanism

B. *Interactions in the CSII Mechanism*

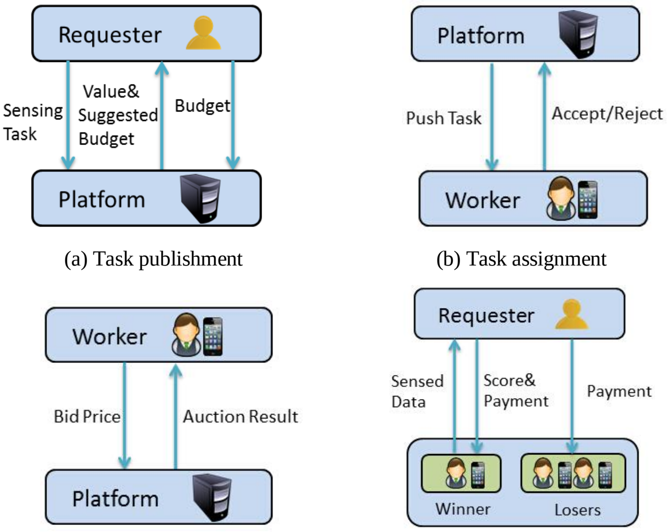
The interactions among the three entities happening at different stages are depicted below.

The interaction between the requester and the platform in the stage of task publishment is shown in Fig. 2(a). In this round of interaction, the requester firstly submits a sensing task description to the platform. The platform estimates its value and budget and then sends back to the requester. Based on the suggested task evaluation infomation, the requester adjusts the number of participants needed.

The interaction between workers and the platform in the stage of task assignment is shown in Fig. 2(b). In this round of interaction, the platform firstly selects workers suitable for the task based on spatio-temporal contexts, and then assigns the task to them. A selected worker can decide whether the task should be accepted. The platform will find additional workers if there are workers who refuse to act, and this process stops when the given number of needed participants is met or there is no one to be evaluated.

The interaction between workers and the platform in the stage of winner selection is shown in Fig. 2(c). In this round of interaction, the workers submit their claimed bid prices to the platform. The platform finds the winner by considering both the bid price and user-reputation. After winner selection, the platform notifies the result to all the workers.

The interaction between the requester and workers in the stage of payment is shown in Fig. 2(d). In this round of interaction, the requester scores the data contributed by the winner. The winner's reputation is updated based on the score. At last, the requester pays the winner and losers respectively.



(a) Task publishment (b) Task assignment

(c) Winner selection (d) Payment mediation

Fig.2. The multiple interactions among the three entities in the stages

C. The Usage of Cross-Space Data

The CSII is on the whole a cross-space collaboration system which uses a combination of physical space infomation and cyber space knowledge for MCS task management and human incentiving.

In particular, at least the task publishment stage and the task assignment stage benefit from the usage of cross-space data. In the stage of task publishment, the platform estimates the task value based on the community behavior information (learned from the check-ins from online LBSN) data and the physical elements of a MCS task (where to sense, what time period to act) offered by the requester. In the stage of task assignment, the platform estimates the performance of workers based on the individual behavior info (according to her LBSN check-ins) and the physical task specification. As is shown in Fig.1, the task management platform acts as mediator for cross-space data collection and fusion.

IV. The Design and Implementation of CSII

As presented in section III, CSII consists of four stages. In this section we present the design and implementation of the four stages.

A. Task Publishment

This module provides the requester and workers objective knowledge about the sensing task's value, which acts as a metric for the suggested budget and worker's claimed bid price. The value of the task is evaluated by addressing several revlant factors, which are parameterized as square-hot and time-hot. Square-hot denotes the popularity of a square region and time-hot denotes the popularity of a sensing period. In this paper, we define that when a square region and a sensing period is popular, the task within the square region and the sensing period is easy to be executed, which implies a low task value. The calculation methods of square-hot and time-hot are presented as follows.

The square-hot of square region *o* is symbolized as *H(o)*, which is calculated as (1). *H(o)* is measured by the number of visitors and check-in frequency. In (1), $VT_{u,j}$ denotes the number of visit times at location *j* of worker *u*; if worker *u* has visited the square *k*, the value of $VU_{u,k}$ is 1, otherwise it is 0. *U* is the set of the whole workers in the CSII mechanism; *Γ* is the set of locations visited by the workers in the set *U*; *K* is the set of square regions covered by the locations in set *Γ*; *AR* is the dimension of the square region *o*.

$$H(o) = \left(\frac{\sum_{u\in U, j\in o} VT_{u,j}}{\sum_{u\in U, j\in \Gamma} VT_{u,j}} + \frac{\sum_{k=o} VU_{u,k}}{\sum_{k\in K} VU_{u,k}} \right) \Big/ AR \tag{1}$$

The square-hot of the sensing task is symbolized as F_C, which is calculated as (2). F_C denotes the visit frequency at square *o* of all workers in set *U* in the valid period of the task. Since the check-in time is flexible, we divide one day into 24 time slots, with each slot being one hour. The check-in time will be represented by time slot 1 to time slot 24, and in (2) we have *T*={1, 2 , 3 … 23, 24}. Hence, according to the start-time *s* and the deadline *d* we can get time-slot coverage set *C* for the sensing task, $C = \{c_1, c_2 \ldots c_{(d-s)}\}, 1 \le s \le 24, (d-s) \ge 1$.

$$F_C = \sum_{t\in C} \frac{\sum_{u\in U, j\in o} VR_{u,t,j}}{\sum_{u\in U, k\in T, j\in o} VR_{u,k,j}} \tag{2}$$

The sensing task is valued with square-hot *H(o)* and time-hot F_C using (3). *AS* is the average square-hot of the total squares in set *K*, and *AT* is the average time-hot of the total time slots in set *T*. We define task value-benchmark to be '1' when the square-hot is *AS* and the time-hot is *AT*, respectively.

Task value-benchmark is a unit value in sensing task evaluation module.

$$v = \frac{AS}{H(o)} * \frac{AT}{F_c} \tag{3}$$

As depicted previously, the platform estimates sensing task value to make an objective budget suggestion to the requester. The suggested budget is calculated using (4), where ($\alpha*v$) is the task compensation paid to the losers in reverse auction (explained in subsection D). In the current stage, the platform has no knowledge about the bid prices claimed by the workers. Hence, we calculate the budget with existing information, e.g., the task value and the number of workers needed. We assume that the payment to the winner is close to the task value. Therefore, the suggested budget is calculated as the sum of the payment to the whole workers who perform the sensing task.

$$B = v + (m-1)*(\alpha * v) \tag{4}$$

B. Task Assignment

In the task publishment stage, the requester specifies the expected number of workers to perform the task. The problem is how to choose suitable people to form the worker group from the human community. It is fulfilled by the worker evaluation module of the CSII mechanism. It assesses whether a worker is appropriate for performing a sensing task according to the worker's check-in history (location and time) and reputation.

The spatio-temporal factor of worker u is denoted as G_u, which is calculated using (5). G_u is measured by the number of visit times at square region o during the task's valid period of worker u. Workers who visite the sensing square region during the valid period of the task are added into set S, and it is empty initially. If worker u satisfies: $u\_l \in o$ and $s \le u\_t \le d$, he is added to set S: $S = S + \{u : u\_l \in o, s \le u\_t \le d\}$. The parameter u_l is the visit location of worker u and the parameter u_t is the corresponding time. In (5), wt_u is the number of visit times of worker u in set S defined in the previous subsection, and $G_u \in (0,1)$.

$$G_u = \frac{wt_u}{\sum_{i \in S} wt_i} \tag{5}$$

The reputation factor of worker u is symbolized as R_u, which is obtained from the database on the platform. R_u is a reflection of the quality about the historical sensed data that worker u submitted to the platform. We assume that the higher a worker's reputation is, the higher quality her collected data is.

In the payment mediation stage below, the requester evaluates the winner's work with score e, based on which the platform updates the reputation for winner u using (6). The score ranges from x to y ($y > x$), and the initial reputation value is 0.5. We assume that the number of winning times in the reverse auction in history for winner u is r and the corresponding reputation is $R_u(r)$.

$$R_u(r+1) = \frac{R_u(r) * r * (y-x+1) + e}{(r+1)*(y-x+1)} \tag{6}$$

The candidates in set S are evaluated using (7), where the value of V_u reflects the suitability for worker u to perform the sensing task. We can obtain that when a worker u holds a high value of V_u, the match of the spatio-temporal contexts between she and the task is high, as well as her reputation.

$$V_u = G_u * R_u \tag{7}$$

We limit the maximum number of tasks that one worker can accept as m_t. The worker whose number of accepted sensing tasks is smaller than m_t and also has checked in at the square o in the valid period will be selected to be evaluated.

The purpose of worker evaluation is to choose a set of suitable workers W to perform a sensing task as sketched in Algorithm 1. The set W is empty initially. The platform sorts the workers in set S in descending order according to the value of V_u and assigns the task to the top one. If the top worker u accepts the sensing task and the number of tasks occupied to her is smaller than m_t currently, the platform adds her into the set W: $W = W + \{u\}$, and assign task to her. We specify that a worker cannot repeat to accept the same task. The above process is iterated until the number of workers in set W reaches the expected number m.

Algorithm 1: Task assignment

Input: A task quadruple T=<m,o,s,d>, set S;

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W ← ∅;
for all u ∈ S do
    Evaluate the worker u to get V_u;
end for
Sort V_u for all u ∈ S in descending order and this list is
    denoted by Ψ;
ζ denotes the head of Ψ;
While the size of W is smaller than m do
    Push task to ζ;
    If ζ accept the task then
        W = W + {ζ};
        Assign the sensing task to ζ;
    end if
    Remove ζ from the list Ψ;
    ζ denotes the head of the new list Ψ;
end while
// The workers in W perform the sensing task
```

C. Winner Selection

When selecting the winner, we take the quality of the sensed data into consideration and assume that reputation can directly reflect the sensed data's quality. Hence, two types of bid prices are used: one is the actual bid price and the other is the competition bid price [12]. The actual bid price b_u is claimed by worker u and the competition bid price w_u is used to select the winner. The competition bid price is defined as (8), where the worker who holds low actual bid price and high reputation will have a higher opportunity to win in the reverse auction. As described in Algorithm 2, the platform sorts the workers in set W in nondecreasing order and selects the top one to be the winner. Then the requester evaluates the winner's work and the platform updates the winner's reputation based on the evaluation as described in previous subsection.

$$w_u = b_u + (1 - R_u) \tag{8}$$

Algorithm 2: Winner selection

Input: Set W;
//Get competition bid
1: **for** all $u \in W$ **do**
2: Submit actual bid b_u;
3: Obtain the reputation R_u of u;
4: $w_u = b_u + (1 - R_u)$;
5: **end for**
// Select winner
6: Sort w_u for all $u \in W$ in the nondecreasing order and the list is denoted by Ω;
7: ξ denotes the head of Ω ;
8: Set ξ as the winner of reverse auction;
//Evaluate the winner's work and pay the rewards
9: Give a score to ξ and update her reputation;

D. *Payment Mediation*

At last, the requester needs to pay the winner and losers as (9). The reward offered to the winner is the average of two values: the winner's actual bid price and the sensing task value. To maintain the losers' willingness in participating in MCS systems, they are paid with task compensation for data collection (The payment scheme is explained in the next section).

$$p_u = \begin{cases} \dfrac{b_u + v}{2} & ; \text{if worker } u \text{ is the winner} \\ \alpha * v & ; \text{if worker } u \text{ is the loser} \end{cases} \tag{9}$$

V. PERFORMANCE ANALYSIS AND EVALUATION

Having presented the detailed design of CSII, in this section we present and discuss its performance over theoretical analysis and experiments.

A. *Analysis of the CSII Mechanism*

The CSII mechanism provides a new incentive mechanism of using cross-space data and interactions among three entities. Before getting into the experiment part, we first give an analysis to explain the main design considerations.

Q1: Why do we need to pay the losers?

A: In CSII, only one worker is selected as the winner. If we just pay the winner for her sensed data, other workers who fail in the reverse auction without reward would lose interest in collecting data in the future. Therefore, task compensation is necessary in mataining the loser's willingness in participation.

Q2: Why does the payment to the winner be the average of her actual bid price and the task value?

A: Our starting point in using the average value as payment is to ensure that the requester's total payment for all the workers, including both the winner and losers, should be as close as possible to the budget suggested by the platform. This setting, as discussed later, is a win-win choice.

When the winner's actual bid price is larger than the sensing task value, if the reward for the winner is set as her actual bid price, the total payment for all the workers is: $p_1 = b_u + (m - 1) * \alpha * v$. If paying the winner the average value, the payment is: $p_2 = 0.5 * (b_u + v) + (m - 1) * \alpha * v$ .The value of p_1 exceeds the suggested budget as: $p_1 - B = b_u - v$, while the value of p_2 exceeds the suggested budget as: $p_2 - B = 0.5 * (b_u - v)$. Paying the winner the average value would make the payment closer to the suggested budget.

On the other hand, when the winner's actual bid price is smaller than the sensing task's value, our payment scheme increases the winner's income compared with his claimed bid price. The winner who adopts the average payment scheme would get more reward than the other scheme presented above, which is calculated as: $0.5 * (b_u + v) - b_u = 0.5 * (v - b_u) > 0$. This may improve the winner's willingness in continuously accepting the sensing task. We regard this setting as a win-win solution because on one hand we can always motive workers' participation by paying the winner almost equivalent price to her expecion, on the other hand we ensure the sustainability of the platform by not allowing the requester's paying too much in one task.

Q3: Why do workers submit bid prices after data collection?

A: There have been studies that bid prices are submitted before data collection. However, it is hard for a worker to estimate how difficult the collection task is and she cannot provide an objective bid price before data collection. Therefore, after performing the sensing task, a worker can offer a relatively objective bid price according to her work experience and the task value suggested by the platform.

Q4: Why do we select m workers for data collection but only the winner submits the data?

A: The reason why we only need the winner to upload the sensing data is that for one single task, large amount of data may cause data redundancy and increase network traffic. The reason why we select m workers for data collection is that a certain number of data collectors can provide a competitive environment, which impels the workers to sense high quality data to win in the reverse auction as well as obtaining a high reputation. The competitive environment also avoids the raising of unreasonable bids in the reverse auction.

Q5: Why do we use reverse auction?

A: In paper [16], Reddy et al. draw conclusions as follows: (1) monetary incentives often increase interest in participating and reinforce good data collection habits. (2) micro-payment [16] based on competition like auction might encourage workers to collect data with high quality. Hence, micro-payment based on reverse auction may be a good choice. In our mechanism, only one winner is needed. The winner might increase her claimed bid price for selling the sensed data to maximize her expected profits. To overcome the challenge, we select the winner by using reverse auction, which could avoid monopoly to restrict worker's claimed bid price closing to her sensing cost.

Q6: Why can the reputation reflect the quality of the sensed data?

A: If the quality of the data collected by the winner is very poor, in the procedure of data quality evaluation, the winner will get a very low score as well as a low reputation. Low reputation will decrease a worker's probability to win in the next task reverse auction. Therefore, people with low reputation may not win in future auctions except that they claim a very low bid price. However, in the long term, if someone always provides poor quality data, she may not win any more in the future even she claims a low actual bid price. Hence, with this mechanism, the one who occupies a high reputation has more chance to win, which ensures the quality of the collected data at the same time.

Q7: Why do we limit the number of accepted tasks for each worker?

A: In CSII, we set that each worker can perform a fixed number of tasks at most at the same time. In reality, there are many requesters publishing tasks, and users with top rankings will be pushed many tasks beyond their ability. To tackle this problem, we propose to limit the number of accepted tasks for every worker. First, we can avoid denunciative users destroying MCS systems by accepting too many tasks but not perform the tasks they claim. This may reduce the quality of data collection and reduce the quality of the service offered by MCS systems. Second, accepting too many tasks will lead to poor data quality or even cause the task unfinished. Limiting the worker's maximal number of tasks can solve this problem. Third, to those workers with high rankings, although they are capable of receiving a large number of tasks, as the number of their accepted tasks is limited, they have to give up some tasks to those workers with average or even low rankings. This is a way to improve the probability of low-ranking workers' accepting a task, as well as avoid workers' dropping out of the system. As a result, this scheme can maintain a certain number of active workers.

B. Simulation Setup

To evaluate the performance of our mechanism, we implement the CSII mechanism with a simulation experiment based on a real check-in data set collected from Jiepang[1] – a popular LBSN website in China. This LBSN dataset contains 966,814 records, 54,148 users, and 33,232 locations, where the check-in longitude and latitude range from 121.21388733 to 121.8059799, and from 31.01791000 to 31.34228544, respectively. We divide the area covered by check-in records into many geographical blocks. The number of check-in records in each block ranges from 1 to 48,419. As the number of check-in locations in some blocks is too small, in the simulation we ignore these blocks whose check-in records are fewer than 1,000. Thus, 28 blocks are used in our simulation, and the check-in record number of the 28 blocks ranges from 1,010 to 48,419.

In the simulation, we set the task limitation of every worker as 5. In every block, 10 different sensing tasks are published, i.e., we have 280 sensing tasks published in total in the whole simulation process. The time slots of the 280 sensing tasks range from 1 to 24, and the number of expected workers is randomly selected from the set {10, 20, 30, 40, 50, 60, 70, 80, 90, 100}. When receiving a sensing task, the worker should decide whether to accept the sensing task or not. We assume that, when the worker's expected reward is larger than β times of her true value [12], the worker would accept the sensing task. Expected reward is calculated using (10). True value denotes the minimum price at which the worker wants to sell the sensed data. Every worker has her true value, which is different from her actual bid.

$$E = \frac{1}{m} * v + \frac{m-1}{m} * \alpha * v \tag{10}$$

In the simulation, the method of generating true value is as follows. There is a task whose evaluated value is the minimum for all tasks published in this block, i.e., the valid period of the task is more than 24 hours. The worker's true value is randomly generated in the form of gaussian distribution where the expectation μ is the minimum task value in her check-in block and the standard deviation σ is 1. If a worker has a check-in record in several blocks, we select the minimum value as the expectation.

We simulate the following three distributions of actual bid price distributions among workers: uniform distribution, exponential distribution, and gaussian distribution. The uniform distribution is abbreviated as $U(a,b)$, where a equals to the true value of a worker and b equals to three times of the task value. The parameter of exponential distribution is the worker's true value, and the actual bid price generated in this method is larger than her true value. For the gaussian distribution, the expectation is the average of the worker's true value and the task value.

When the requester evaluates the sensed data contributed by the winner with the scores ranging from x to y, we set x equals to 1 and y equals to 10 in the simulation. The score given to the winner is generated according to the following rule: the score is larger than 7 with a probability of 60% and is smaller than 7 with a probability of 40%.

C. Evaluation Result

To evaluate the performance of CSII, we use the following metrics: acceptance ratio, overpayment ratio, average profit ratio, and average extraneous earning.

[1] http://jiepang.com

In simulation, two parameters would affect the worker's decision on whether to perform the sensing task: parameter α used in (9) and (10) and parameter β used to make the decision of task acceptance. The values of α and β are as follows.

α={0.01,0.03,0.05,0.07,0.09,0.11,0.13,0.15,0.17,0.19,0.2}

β={0.01,0.05,0.1,0.15,0.2,0.25,0.3}

Figure 3 illustrates how the two parameters α and β affect the worker's decision on accepting the sensing task or not. The acceptance ratio is the percentage of accepted numbers in set *S*, i.e., the number of accepted workers divided by the number of workers in set *S*. We can see that the acceptance ratio decreases with the increasement of β, and increases as α increases. This is because if α takes a large value, the worker's expected reward would increase, which increases her willingness in participation. In Fig. 3, when α takes a value larger than 0.07, no matter what value β is, the acceptance ratio of workers is always greater than 98%. What's more, the expenditure of the requester will increase with the increasement of α. Therefore, we set α=0.03, β=0.15 in the later evaluation, where the acceptance ratio is larger than 98%.

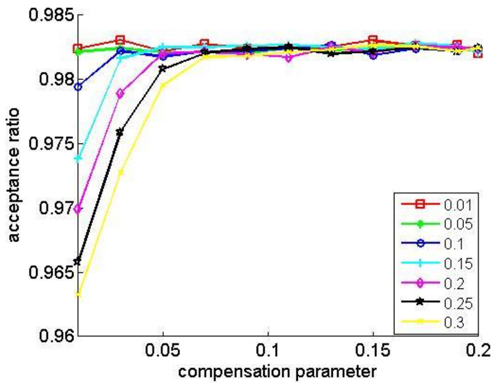

Fig.3. The acceptance ratio affected by compensation parameter α and accepted decision parameter β, x-axis is compensation parameter and different polylines represent different β

In our simulation, 10 tasks are published in every block. We select 28 blocks to illustrate the requester's overpayment ratio with three different actual bid price distributions. If the overpayment ratio is negative, the payment to all the workers is smaller than the suggested budget. Otherwise, the payment is larger than the budget.

Figure 4 shows the average overpayment of the 10 tasks published in each block. Only the 27th block's average overpayment is positive under the exponential distribution, which means that our CSII mechanism can provide a good budget suggestion within the total payment. Among the three distributions, the overpayment ratio of the exponential distribution is the biggest while the overpayment ratio of gaussian distribution is the smallest. This is because the actual bid price under the uniform distribution has a bigger probability to have a higher value than other distributions. In uniform distribution, the biggest value the actual bid price can take is three times of the task value. In gaussian distribution, although the actual bid price can be larger than three times of the task value, the probability of this situation is very small with the standard deviation σ being 1. In conclusion, no matter what distributions is used, their majority average overpayment is below zero.

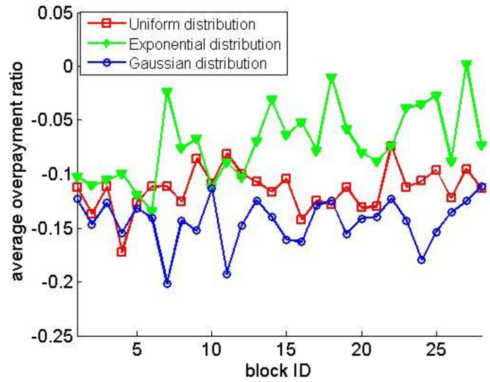

Fig.4. The average overpayment ratio under three different distributions in the 28 blocks

We assume that the true value represents the cost that a worker spends on performing the sensing task. Under the assumption, the profit for the winner is defined as the difference between the reward she obtains and her true value. Extraneous earning is defined as the difference between the reward and her actual bid price, which is the extra earning people obtains than her initial expectation. Figure 5 shows the average profit of the winners in each block. The results of the three distributions are greater than zero, indicating that no matter what distribution the bid price follows, most winners would have a positive profit and benefit from her work. Figure 6 illustrates the average extraneous earnings of the winners, where the average extraneous earnings of 10 sensing tasks of each block is larger than zero except for the 9th block under uniform distribution. Most winners can get more reward than their initial expectations, which also applies to the losers, since they might get nothing compared to other incentive mechanisms. Benefiting from the CSII mechanism can improve the willingness of user participation.

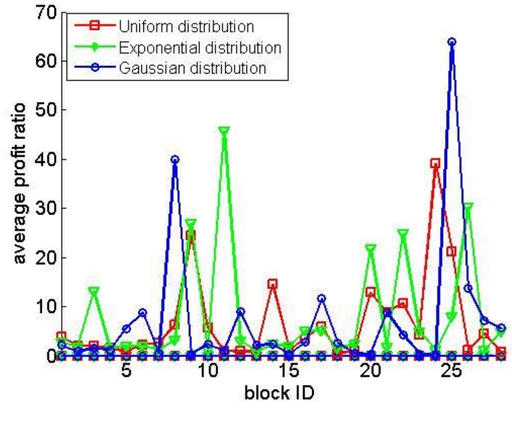

Fig.5. Average profit ratio under three distributions in the 28 blocks

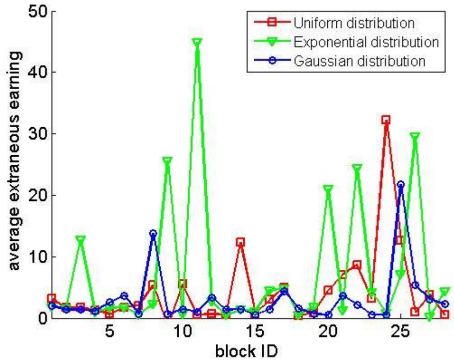

Fig.6. Average extraneous earning under three distributions in the 28 blocks

We obtain the average reputation of the winners for the 10 sensing tasks in each block. The average reputation of the winners in each block is shown in Fig. 7, in which the average reputation is larger than 0.66. Since the winner is selected based on two factors—reputation and actual bid price, the reputation of the winner may not be the highest of all workers. However, as demonstrated by Fig. 7, the reputation of selected winners remains at a relatively high level (reputation > 0.66), which indicates that our proposed method can ensure the quality of sensed data.

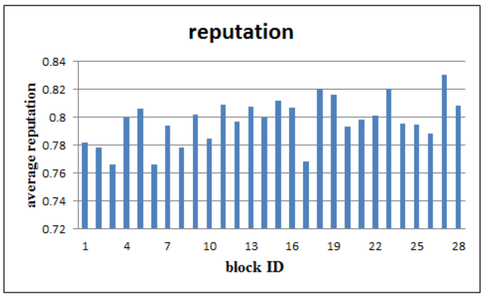

Fig.7. Average reputaiton of the winners in 280 tasks in different blocks

VI. CONCLUSION

In this paper, we have designed a new incentive mechanism for mobile crowd sensing systems called CSII. It leverages the interactions among requesters, the task management platform, and selected workers to achieve dynamic budget, optimal task allocation, and high willingness on participation. In addition, a combination of online and offline data have been explored in CSII for task value estimation and worker selection. Experiment results indicate that CSII succeeds in making a tradeoff between maintaining a certain number of workers and in making the payment of the requester approximately within the suggested budget. As for future work, we will deploy the mechanism in real world MCS systems (like our project FlierMeet [17]) and evalutate its performance in practice. Also, we intend to consider about other factors that impact user participation, such as user preference and privacy protection, and improve the CSII mechanism.

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