Free Market of Crowdsourcing: Incentive Mechanism Design for Mobile Sensing

Xinglin Zhang, *Student Member, IEEE*, Zheng Yang, *Member, IEEE*, Zimu Zhou, *Student Member, IEEE*, Haibin Cai, Lei Chen, *Member, IEEE*, and Xiangyang Li, *Senior Member, IEEE*

Abstract—Off-the-shelf smartphones have boosted large scale participatory sensing applications as they are equipped with various functional sensors, possess powerful computation and communication capabilities, and proliferate at a breathtaking pace. Yet the low participation level of smartphone users due to various resource consumptions, such as time and power, remains a hurdle that prevents the enjoyment brought by sensing applications. Recently, some researchers have done pioneer works in motivating users to contribute their resources by designing incentive mechanisms, which are able to provide certain rewards for participation. However, none of these works considered smartphone users' nature of opportunistically occurring in the area of interest. Specifically, for a general smartphone sensing application, the platform would distribute tasks to each user on her arrival and has to make an immediate decision according to the user's reply. To accommodate this general setting, we design three online incentive mechanisms, named TBA, TOIM and TOIM-AD, based on online reverse auction. TBA is designed to pursue platform utility maximization, while TOIM and TOIM-AD achieve the crucial property of truthfulness. All mechanisms possess the desired properties of computational efficiency, individual rationality, and profitability. Besides, they are highly competitive compared to the optimal offline solution. The extensive simulation results reveal the impact of the key parameters and show good approximation to the state-of-the-art offline mechanism.

Index Terms—Crowdsourcing, incentive mechanism, mobile sensing

1 Introduction

The market of smartphones has proliferated rapidly in recent years and continues to expand. According to the International Data Corporation (IDC) World-wide Quarterly Mobile Phone Tracker, 216.2 million smartphones are shipped in the first quarter of 2013 [1]. IDC expects that the smartphone shipments will grow by nearly 15.8 percent and approach 63 percent of device shipments in 2016 [2].

The era of smartphones brings more than just quantity. Today's hand-held devices possess powerful computation and communication capability, and are equipped with various functional built-in sensors. Along with users round-the-clock, mobile phones have become an important information interface between users and environments. These advances enable and stimulate the development of smartphone-based sensing technologies [3], [4]. Highlighting the participation of smartphone users, this paradigm falls into the scope of participatory sensing, which has attracted many research efforts in the field of mobile and pervasive computing.

Participatory sensing emphasizes the involvement of a large amount of participants in the process of sensing and documenting where they live, work, and play. By synthesizing ample information including images, sounds, mobilities, locations, and travel records, it is possible to reveal hidden habits and patterns in one's life or public behavior related to health, safety, social dynamics, and cultural identity. In this sense, participatory sensing opens a window onto life and society that allows one to reflect on, evaluate, and perhaps change patterns that were previously overlooked. Pioneer works include VTrack [5] and SignalGuru [6] for traffic monitoring, NoiseTube [7] for noise monitoring, SmartTrace [8], CityExplorer [9], Sensorly [10] for 3G/WiFi discovery, Co-evolution model [11] for behavior and relationship discovery, Frequent Trajectory Pattern Mining [12] for activity monitoring, LiFS [13] for indoor localization, crowd-participated system [37] for Q1 bus arrival time prediction, etc.

In most of the above-mentioned applications, a smartphone user is moving and sensing opportunistically in the area of interest. Therefore, users may exhibit temporal variations in replying the sensing tasks. For example, in Pothole Patrol [14], the system tries to detect surface conditions of roads by assigning tasks to participating vehicles that pass by the roads one by one stochastically. Similarly, in [15], The noise mapping system publishes tasks to sequentially occurring smartphone users. In summary, participatory sensing applications reflect the essential and unique mobile nature of smartphone users.

The power of participatory sensing relies on the quality and quantity of its participants, yet it is simply over-optimistic to envision a planet-wide sensing platform at hand. The

- *X. Zhang, Z. Zhou, and L. Chen are with the Department of Computer Science and Engineering, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong. E-mail: {zhxlinse, zhouzimu.hk}@gmail.com, leichen@cse.ust.hk.*
- *Z. Yang is with the School of Software and Tsinghua National Lab for Information Science and Technology, Tsinghua University, Beijing, China. E-mail: hmilyyz@gmail.com.*
- *H. Cai is with the Software Engineering Institute, East China Normal University, Shanghai, China. E-mail: hbcai@sei.ecnu.edu.cn.*
- *X. Li is with the Department of Computer Science, Illinois Institute of Technology, 10, West 31st Street, Chicago, IL 60616. He is also with the Department of Computer Science and Techonlogy, and TNLIST, Tsinghua University, Beijing, China. E-mail: xli@cs.iit.edu.*

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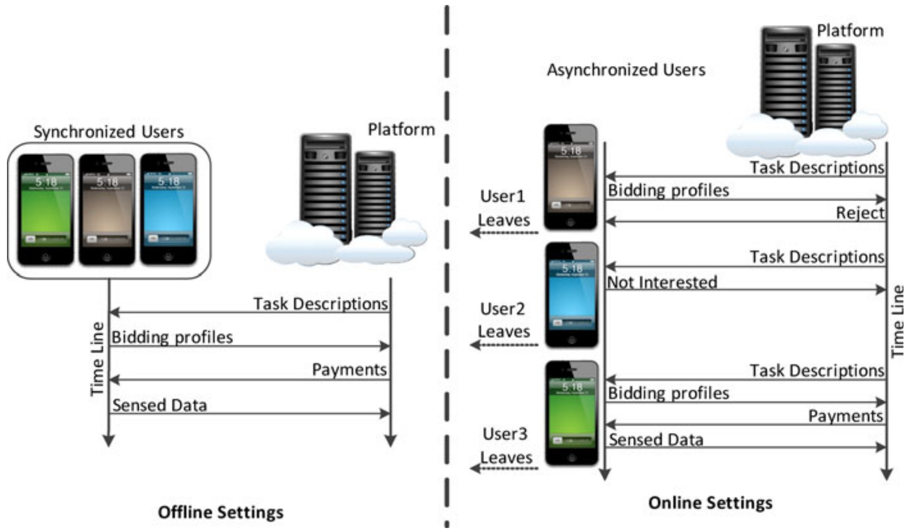

Fig. 1. Offline/online settings for smartphone crowdsourcing.

main hurdle lies in the lack of efficient incentive mechanisms. More concretely, in existing works, the participants are researchers or volunteers, and thus their willingness of participation is not an issue at all. When extending participants from professionals to ordinary individuals, however, the assurance of their willingness of contribution is indeed a critical problem. The employed smartphones to sense the environment will consume their own resources of computation, communication, and energy. Therefore, it is natural that users will not participate in the sensing task, unless they are sufficiently motivated. That is, the scale of participatory sensing will not reach large, hence departing from its original imagination, without effective incentive mechanisms.

The mobile nature of these distributed computation and sensing powers further complicates the incentive mechanism design. In brief, it is common in practical mobile sensing that users are coming and bidding for a specific task *sequentially*, and the decision on accepting or denying a user's bid must be made by the platform *instantly* upon the user's arrival, as illustrated on the right side in Fig. 1. Nevertheless, pioneer works on incentive mechanism (e.g., [16]) are *static* and *offline*, in which the *concurrent* presence of numerous smartphone candidates is required. These offline schemes assume that all users will stay from the very beginning of one round of task distribution for bidding and cannot accept new bids afterwards (shown on the left side in Fig. 1). In other words, the offline mechanisms all fail in a more practical yet dynamic setting of mobile phone sensing. We hence explore to devise a new thread of *online* incentive mechanisms.

In this work, we will first design two online incentive mechanisms based on online reverse auction: threshold-based auction (TBA) and truthful online incentive mechanism (TOIM). Then we extend TOIM to the non-zero arrival-departure model and present the third mechanism TOIM-AD. TBA is designed to pursue utility maximization, while TOIM/TOIM-AD makes a tradeoff between utility maximization and truthfulness. Simulation results validate the desired properties of the mechanisms, reveal the impact of the key parameters, and show good approximation to the state-of-the-art offline mechanism.

The key contributions of our work are summarized in the following:

- To the best of our knowledge, this is the first work on *online* incentive mechanism design for crowd-sensing applications with smartphones, where the platform does not have to synchronize large amounts of users simultaneously while distributing tasks. The online attribute of the devised mechanisms offers more flexibility in recruiting opportunistically encountered participants and holds potential for practical and large-scale mobile sensing applications.
- We design three online incentive mechanisms: TBA, TOIM and TOIM-AD. These mechanisms are computationally efficient, individually rational, profitable and highly competitive. What's more, TOIM and TOIM-AD possess the essential property of truthfulness.
- Extensive simulations have validated the viability of the proposed incentive mechanisms and the analysis of the key parameters gives guidance for tuning the mechanisms to meet application requirements.

The rest of the paper is organized as follows. Section 2 formulates the system model and problem. The proposed online incentive mechanisms are described in Section 3. Section 4 shows the performance of the proposed mechanisms. Finally, Section 5 reviews related work and Section 6 concludes this paper.

2 Problem Formulation

Fig. 1 illustrates the typical interaction flow of both the offline and online settings in smartphone crowd-sensing system. The system involves two participating roles: the *platform* that distributes a sensing task and the mobile phone *users* who constitute potential labor force. The objective is to design a task assignment scheme which ensures both the platform and the users are satisfied, i.e., their utility functions are maximized. We elaborate the interaction procedures under the two settings separately.

In the offline setting (on the left side of Fig. 1), the platform initiates one round of task distribution by sending *task descriptions*. And a set of n users are assumed to be interested in the sensing tasks after receiving the requests. As the sensing task consumes their own resources of computation, communication, and energy, the participating users incur a *cost*. It is thus rational for each user to expect certain profit based on her cost and sensing plan (e.g., the sensing time). A participating user then submits a *bidding profile* (including the bidding price and the sensing plan) to the platform. The platform decides which users to accept and offers the *payments* to the users after collecting all bidding profiles from the n users. And the paid users then perform the assigned tasks and return the sensed data back to the platform.

Unlike the batched and synchronised manner in the offline setting, the interactive process in the online setting is sequential and asynchronous. Before recruiting any users for sensing tasks, the platform first decides the expected number of participating users needed for a particular sensing task m. And it will recruit users within the first n applying users who are interested in the task. The key difference is that the decision of the platform is made one by one upon each user's arrival in a random order. And each user leaves immediately after one round of interactions with the platform. The interactive procedures between the platform and each of the potentially participating users is summarized as follows (illustrated on the right side of Fig. 1):

- The platform sends the sensing *task description* to mobile phone user who opportunistically steps into the targeted sensing area.
- The user receives such a message. If she is not interested in the sensing task, she will simply ignore the message; otherwise, she will submit a *bidding profile* including the bidding price and sensing plan back to the platform.
- The platform receives a bidding profile and has to make an *irrevocable* decision regarding whether or not to accept the bid and distribute a *payment* to the accepted user.
- The chosen user conducts the assigned sensing tasks and returns the corresponding data to the platform. And this completes the interaction between one user and the platform.

In the online setting, one round of task assignment finishes until the platform has recruited m users to perform the sensing task. Note that in this setting, the number n reflects the time requirement of completing the task, and the recruit number m helps to motivate users to compete for winning the auction. Both parameters are given according to the specific crowdsensing task requirement. In this setting, we implicitly assume large amounts of users are willing to participate, as the crowdsourced tasks are trivial for smartphone users and can bring users profit [17], [18], [19], [20]. Under this assumption, the incentive mechanism works by controlling the interaction between the platform and bidding users.

We interpret several key parameters in the above interaction processes here. Typically, a *bidding profile* specifies a user's *bidding price* and *sensing plan*. The *bidding price* of a user is the minimum price that she will accept for exchange of her sensing effort. The price is a real value generated according to the sensing plan. And the *sensing plan* is scenario-specific. For instance, in [16], a sensing plan describes a user's willingness on how long she wants to involve in the sensing task, i.e., the sensing time of each user. Another example is provided in [17], where the task may contain several assignments. The sensing plan thus shows how many assignments a bidder is willing to take.

TABLE 1
Notations

Symbol	Description
$\mathcal{T},\mathcal{U}$	set of winning users, set of potential users
$\mathcal{Q}$	set of users before cutoff number
m, n	number of winning users, number of all potential users
k	cutoff number for changing to submodular threshold algorithm
v_i	value brought by user i to the platform
b_i, c_i	the bid price and true cost of user i
p_i	payment given by the platform to user i
$\tilde{u_i}, u$	utility of user i, utility of the platform
$u_i(\mathcal{T})$	marginal utility increment by adding user i to the winning set $\mathcal{T}$
α	tradeoff parameter controlling the number of recruited users before cutoff number
ε	parameter used for computing the marginal utility threshold
e	base of the natural logarithm
a_i/d_i	arrival/departure time of user i

As previously discussed, the objective of the incentive mechanism is to ensure both the platform and the users are satisfied. And this is evaluated by their own *utilities*. Both the platform and participating users are interested in pursuing high utility. From the perspective of the platform, users' sensing plans and the corresponding bid prices are input for its strategy, and it evaluates its utility gained from a specific user before deciding whether to recruit and pay the user or not. On the user's side, she also evaluates her utility based on the cost to conduct the assigned sensing task.

We mathematically formulate the incentive mechanism problem for online smartphone crowdsensing in the subsequent section and the frequently used notations are summarized in Table 1.

2.1 Mathematical Formulation

Assume that user i has a true cost of c_i, and she bids at a price b_i when receiving the task message sent by the platform. c_i and b_i are i.i.d. sampled from some unknown distribution. We assume that users are coming to submit their bids in a random order. If the platform accepts the bid of user i, it determines a payment price p_i, and adds user i to the set $\mathcal{T}$ of winning users. Then the utility of user i is

$$\tilde{u_i} = \begin{cases} p_i - c_i, & \text{if} \quad i \in \mathcal{T}, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

The expected utility of the platform is

$$u = \lambda \cdot \log\left(1 + \frac{v(\mathcal{T})}{\lambda}\right) - b(\mathcal{T}), \tag{2}$$

where $v(\mathcal{T}) = \sum_{i \in \mathcal{T}} \upsilon_i$ and $b(\mathcal{T}) = \sum_{i \in \mathcal{T}} b_i$.

The log term in Equation (2) captures the platform's marginal diminishing return on selected users, which conforms to the usual economic assumption [21]. λ is a system parameter that can control the gradient of the diminishing return. υ_i is the value brought by user i to the platform. The calculation of υ_i depends on specific applications. For example, in [16], υ_i is evaluated through the sensing time submitted by user i. And in [22], υ_i depends on the locations of user i through a coverage function. Note that the actual payment given to user i may be greater than b_i, i.e., $p_i \geq b_i$. To make the problem meaningful, we assume that the platform can recruit at least one user i such that $u(\{i\}) > 0$.

As with Yang et al. [16], our objective is to design an online incentive mechanism with the following four properties:

- *Computational efficiency*. An online mechanism is computationally efficient if it has a polynomial time complexity.
- *Individual rationality*. A user will get nonnegative utility upon completing the sensing task.
- *Profitability*. The platform will get nonnegative utility at the end of the sensing task.
- *Truthfulness*. A mechanism is truthful, or incentive compatible, if a bidder cannot improve her utility by submitting a bidding price deviating from her true value in spite of others' bidding prices.

The first three properties guarantee the feasibility of the incentive mechanism, while truthfulness makes the mechanism free from market manipulation and encourages users to reveal their true value. Note that we adopt these properties as they are essential in the sense of designing incentive mechanisms, no matter in the online setting or in the offline setting. In addition, we will examine the mechanisms with one more property:

- *Competitiveness*. To evaluate the performance of the mechanism considering utility maximization, we compare its solution with the optimal solution in the offline setting, where the platform has the full knowledge of users' bidding profiles. A mechanism is $O(g(n))$-competitive if the ratio between the online solution and the optimal offline solution is $O(g(n))$.

3 Online Incentive Mechanisms

In this section, we will develop three online incentive mechanisms, named TBA, TOIM, and TOIM-AD. These mechanisms investigate the desirable properties of the incentives from different perspectives. The basic idea of TBA is to use the first batch of bidders as a reference set and make recruitment decisions on the second batch of bidders. TBA puts strength in maximizing the platform utility, which provides a performance upperbound for TOIM and TOIM-AD. Based on the structure of TBA, we design TOIM and TOIM-AD. TOIM is a truthful online mechanism which is highly competitive to the optimal solution in the zero arrival-departure model; while TOIM-AD extends TOIM to the non-zero arrival-departure model.

3.1 Threshold-Based Auction

First, we attempt to design an online auction-based incentive mechanism maximizing the platform's utility, which is an online optimization problem. Babaioff et al. [23] presented a framework based on generalized secretary problems for online auctions, which could only achieve approximation algorithms. In our problem, as the objective function is more complex, the optimization is more difficult. We will resort to the property of submodularity in developing the auction mechanism.

Definition 1 (Submodular Function). *Given a groundset Ω, a function $f : 2^{\Omega} \rightarrow R$ is submodular if for any $\mathcal{A} \subseteq \mathcal{B} \subseteq \Omega$, and $e \in \Omega$, we have*

$$f(\mathcal{A} \cup \{e\}) - f(\mathcal{A}) \geq f(\mathcal{B} \cup \{e\}) - f(\mathcal{B}).$$

For the sake of simplicity, we denote $f(\mathcal{A} \cup \{e\}) = f(\mathcal{A} + e)$ and $f_e(\mathcal{A}) = f(\mathcal{A} + e) - f(\mathcal{A})$.

Lemma 1. *The platform utility u is submodular.*

The proof of Lemma 1 is given in the supplementary file of the paper, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TPDS.2013.2297112.

Having proved the submodularity of the utility function, we would like to design an auction mechanism based on the algorithm of [24]. However, the utility function u can be negative, which does not meet the requirement of the algorithm. To ensure the nonnegativity of the objective function, we replace u with $u + \sum_{i \in \mathcal{Q}} b_i$ to run the offline submodular maximization algorithm, where $\sum_{i \in \mathcal{Q}} b_i$ is a constant obtained from the groundset $\mathcal{Q}$. The nonnegativity comes from the following direct intuition. Given any set $\mathcal{T}$ of selected users, where $\mathcal{T} \subseteq \mathcal{Q}$, we have $u + \sum_{i \in \mathcal{Q}} b_i \geq u + \sum_{i \in \mathcal{T}} b_i = \lambda \log(1 + \frac{v(\mathcal{T})}{\lambda}) \geq 0$. From the optimization point of view, maximizing both objectives are equivalent. And the discussion of competitiveness will be based on this revised objective function.

We thus develop an online incentive mechanism called threshold-based auction (TBA), as illustrated in Algorithm 2. The first k users' bidding profiles, as well as the expected recruitment number m and the utility function u, will be collected as input to run the offline submodular maximization algorithm $SubmodMaxCardinality$ (Algorithm 1), which gives an estimate of the optimal value of selecting m users. Specifically, the algorithm makes use of two subroutines to generate several candidate sets and returns the one with the largest utility (Lines 2 to 7). Each subroutine takes $\mathcal{Q}$ as the groundset and the function $f = u + \sum_{i \in \mathcal{Q}} b_i$ as the objective function. Subroutine $Greedy$ makes use of the greedy strategy to select m users, while $FMV_{2.5}$ applies a local search algorithm (the analysis of these two subroutines are involved and we refer interested users to [24], [25] for more detailed discussion).

Given the set $\mathcal{S}$ of selected users, Lines 8 to 12 calculates the marginal utility increment vector $\delta = [\delta_1, \delta_2, \ldots, \delta_{|\mathcal{S}|}]$ by greedily selecting the user with the largest marginal increment. δ is further used to construct a marginal utility threshold value with an approximate value ε, which is determined by the platform. The users having marginal utilities above the threshold will be selected and be paid a reward equalling their bidding prices, until the platform has recruited the desired number of users.

Algorithm 1 SubmodMaxCardinality($\mathcal{Q}, m, u$)

1: $\mathcal{Q}_1 \leftarrow \mathcal{Q}, f \leftarrow u + \sum_{i \in \mathcal{Q}} b_i$;
2: **for** $i = 1$ **to** 2 **do**
3: $\quad \mathcal{P}_i \leftarrow Greedy(\mathcal{Q}_i)$;
4: $\quad \mathcal{P}'_i \leftarrow FMV_{2.5}(\mathcal{P}_i)$;
5: $\quad \mathcal{Q}_{i+1} \leftarrow \mathcal{Q}_i \backslash \mathcal{P}_i$;
6: **end for**
7: $\mathcal{S} \leftarrow$ best of $\mathcal{P}_1, \mathcal{P}'_1, \mathcal{P}_2$;
8: $\mathcal{S}' \leftarrow \phi$;
9: **for** $i = 1$ **to** $|\mathcal{S}|$ **do**
10: $\quad j \leftarrow \arg\max_{j' \in \mathcal{T}} u_{j'}(\mathcal{S}')$;
11: $\quad \delta_i = \max\{u_j(\mathcal{S}'), 0\}; \mathcal{S}' \leftarrow \mathcal{S}' \bigcup \{j\}; \mathcal{S} \leftarrow \mathcal{S} \backslash \{j\}$;
12: **end for**

Algorithm 2 Threshold-based Auction (TBA)

1: $\mathcal{T} \leftarrow \phi, k = n/2$;
2: observe first k users constituting set $\mathcal{Q}$;
3: $\delta \leftarrow SubmodMaxCardinality(\mathcal{Q}, m, u)$;
4: $i \leftarrow k + 1$;
5: **while** $i < n$ **and** $|\mathcal{T}| < m$ **do**
6: $\quad$ **if** $u_i(\mathcal{T}) \geq \frac{\delta_{|\mathcal{T}|+1}}{\varepsilon}$ **then**
7: $\quad\quad \mathcal{T} \leftarrow \mathcal{T} \bigcup \{i\}; p_i \leftarrow b_i$;
8: $\quad$ **end if**
9: $\quad i \leftarrow i + 1$;
10: **end while**

Next we analyze the properties of TBA algorithm.

- *Computational efficiency.* In TBA algorithm, the while-loop is of $O(n)$ time complexity. On the other hand, the function *SubmodMaxCardinality* is of $O(\frac{1}{\epsilon} n^3 m \log m)$ time complexity [24]. Thus TBA can be computed in polynomial time.
- *Individual rationality.* In TBA algorithm, the winning users will be given payments equalling to their claimed bids. As users are assumed to be selfish and rational, their bids must be no less than their true costs. Therefore, the users who are recruited will have nonnegative profit.
- *Profitability.* Lines 6 and 7 of TBA algorithm assure that the platform will have nonnegative marginal utility when it recruits a user. So at the end of the algorithm, the total utility of the platform is nonnegative.
- *Truthfulness.* We use a simple example here to demonstrate that TBA is untruthful. Suppose that we want to select 2 users in the next 5 users. We have calculated the marginal threshold vector $opt = \frac{\delta}{\varepsilon} = [8, 6]$ from the observation of the previous users. And the system parameter $\lambda = 500$. The set of winning users is $\mathcal{T} = \phi$ at the beginning. The value and bid price of the users are listed in Table 2.

TABLE 2
An Example Showing the Untruthfulness of TBA

i	1	2	3	4	5
b_i	3	5	6	4	7
υ_i	10	5	7	9	7

(a) Users bidding truthfully

i	1	2	3	4	5
b_i	3	5	6	4+ϵ	7
υ_i	10	5	7	9	7

(b) User 4 is untruthful, with bidding 4+ϵ, where $0 < \epsilon \leq 2.61$

Assume that the users are bidding truthfully. Since $u_1(\mathcal{T}) = \lambda \log(1 + \frac{\upsilon_1}{\lambda}) - b_1 = 11.28 > opt_1 = 8$, then TBA adds user 1 to the target set, i.e., $\mathcal{T} = \{1\}$. Next TBA calculates the marginal utility obtained by adding user 2, $u_2(\mathcal{T}) = \lambda \log(1 + \frac{\upsilon_1 + \upsilon_2}{\lambda}) - (b_1 + b_2) - u(\mathcal{T}) = 2.04 < opt_2 = 6$. User 2 is not satisfied. TBA ignores user 2 and considers user 3. Using the same procedure, we get $u_3(\mathcal{T}) = 3.83 < opt_2$ and $u_4(\mathcal{T}) = 8.61 > opt_2$. Therefore, TBA selects user 4 and the algorithm terminates.

Now assume that user 4 lies by bidding $4 + \epsilon$ (Table 2b), where $0 < \epsilon \leq 2.61$. The calculation for the first 3 users are the same. For user 4, $u'_4(\mathcal{T}) = \lambda \log(1 + \frac{\upsilon_1 + \upsilon_4}{\lambda}) - \lambda \log(1 + \frac{\upsilon_1}{\lambda}) - (4 + \epsilon) = u_4(\mathcal{T}) - \epsilon \geq 8.61 - 2.61 = 6 = opt_2$. Thus, user 4 is still qualified. The platform selects user 4 and the payment is up to 6.61. In this case, user 4 increases her payment by lying about her true cost, which demonstrates that TBA is untruthful.

We summarize the competitiveness of TBA in Lemma 2.

Lemma 2. *TBA is $O(\frac{1}{\varepsilon})$-competitive.*

Proof. Let $\mathcal{T}^*$ be the best user set selected by the offline submodular maximization algorithm *SubmodMax Cardinality* with repsect to the entire candidate user set $\mathcal{U}$. The utility of $\mathcal{T}^*$ is thus $u(\mathcal{T}^*)$, which has been proved to be $O(1)$-competitive compared with the optimal solution [24]. Hence we only need to show that TBA has a competitive ratio $O(\frac{1}{\varepsilon})$ compared with $u(\mathcal{T}^*)$. Then TBA is also $O(\frac{1}{\varepsilon})$-competitive compared with the optimal solution.

Let $\mathcal{T}_1$ and $\mathcal{T}_2$ be the subsets of $\mathcal{T}^*$ that appear before and after the cutoff value $k = n/2$, respectively. The set of users observed before cutoff value is denoted as $\mathcal{T}_b$. Thus we have $\mathcal{T}_1 = \mathcal{T}^* \cap \mathcal{T}_b$ and $\mathcal{T}_2 = \mathcal{T}^* \cap \{\mathcal{U} \backslash \mathcal{T}_b\}$. Since the costs and values of users in $\mathcal{U}$ are independent and identically distributed, they can be selected in $\mathcal{T}^*$ with the same probability. Also, the sampled set $\mathcal{T}_b$ is a random subset of $\mathcal{U}$ as users come to submit their bids in a random order. Therefore, the number of users from $\mathcal{T}^*$ in the set $\mathcal{T}_b$ conforms to a hypergeometric distribution $H(n/2, |\mathcal{T}^*|, n)$. Hence we have $\mathbb{E}[|\mathcal{T}_1|] = \mathbb{E}[|\mathcal{T}_2|] = |\mathcal{T}^*|/2$. The utility of each user can be seen as an independent and identically distributed random variable. Combining the submodularity of u, it can be derived that

$$\mathbb{E}[u(\mathcal{T}_1)] = \mathbb{E}[u(\mathcal{T}_2)] \geq u(\mathcal{T}^*)/2. \tag{3}$$

On the other hand, when TBA goes to Line 3 and implements offline submodular maximization considering the users that have been observed, it can obtain a best user set $\mathcal{T}'$. Thus we have

$$\mathbb{E}[u(\mathcal{T}')] \geq \mathbb{E}[u(\mathcal{T}_1)] \geq u(\mathcal{T}^*)/2. \tag{4}$$

For an appropriate value of ε, the platform can recruit expected number of m users. Denote $\mathcal{T}$ as the user set selected by TBA. Then after executing the while loop from Lines 5 to 10, we accumulate m inequalities and have

$$u(\mathcal{T}) \geq \sum_{t=1}^{|\mathcal{T}|} \delta_t/\varepsilon \geq u(\mathcal{T}')/\varepsilon. \tag{5}$$

Combining inequalities (4) and (5) gives the result $\mathbb{E}[u(\mathcal{T})] \geq u(\mathcal{T}^*)/2\varepsilon$, which means that TBA mechanism is $O(\frac{1}{\varepsilon})$-competitive compared with the offline solution. □

3.2 Truthful Online Incentive Mechanism

TBA algorithm aims at approximately maximizing the platform's utility by employing submodularity. However, TBA is untruthful, which may encourage users to lie about their true costs in order to get higher profit. On the other hand, the sampling period ignores the first batch of users before the cutoff number k (Line 3 of Algorithm 2), which makes TBA algorithm less attractive, as in this setting, users may tend to arrive later so that they can have more chances to win the bidding. This may make the platform delay the completion of the task or even starve as it cannot receive any bids.

Considering these factors, we develop a truthful online incentive mechanism (TOIM) which sacrifices some utility while maintaining the essential truthfulness of the mechanism as well as facilitating fast completion of the task.

TOIM is illustrated in Algorithm 3. Before the cutoff number k (Lines 4 to 9), the algorithm lacks the guidance to decide whether a user is good enough to recruit. The algorithm maintains a set $\mathcal{Q}$ of bids that it has seen so far, and accepts a new bid b_i if $b_i < threshold$, where $threshold \leftarrow CalThreshold(\mathcal{Q})$. ($CalThreshold$ calculates a statistical value, e.g., the mean/median value, from the bids of the observed users). Also, TOIM makes sure that the marginal utility of the platform being nonnegative after the platform pays to the selected user. In this phase, the platform recruited $l = \lfloor \alpha \cdot m \rfloor$ users, where $\alpha \in [0, 1/2)$.

When the platform has encountered k users, TOIM uses all the bids that it has seen so far to run an offline utility maximization algorithm $SubmodMaxCardinality$ (Line 10). Based on the approximate optimal utility obtained from $SubmodMaxCardinality$, TOIM gets a threshold marginal utility increment vector as in TBA. Also TOIM sets a threshold price that it is willing to pay a qualified user. Recall that $u_i(\mathcal{T}) = \lambda \cdot \log(1 + \frac{v(\mathcal{T}+i)}{\lambda}) - \lambda \cdot \log(1 + \frac{v(\mathcal{T})}{\lambda}) - b_i$, then the actual marginal utility of user i is set $u_i(\mathcal{T}) + b_i - threshold$, where $threshold$ is the threshold price that the platform is willing to pay the user. If this marginal utility is higher than the threshold marginal utility, the platform will recruit her (Line 14). The whole procedure of TOIM aims to obtain a high utility of the platform while maintaining truthfulness.

Algorithm 3 TOIM

1: $\mathcal{T} \leftarrow \phi, k = n/2, l = \lfloor \alpha \cdot m \rfloor, r = \lfloor k/e \rfloor$;
2: observe first r users constituting set $\mathcal{Q}$;
3: $threshold \leftarrow CalThreshold(\mathcal{Q}); i \leftarrow r + 1$;
4: **while** $|\mathcal{T}| < l$ **and** $i < k$ **do**
5:   **if** $b_i \leq threshold \leq u_i(\mathcal{T}) + b_i$ **then**
6:     $\mathcal{T} \leftarrow \mathcal{T} \bigcup \{i\}; p_i \leftarrow threshold$;
7:   **end if**
8:   $i \leftarrow i + 1$;
9: **end while**
10: $\delta \leftarrow SubmodMaxCardinality(\mathcal{U}(1:i), m/2, u)$;
11: $j \leftarrow 1$;
12: **while** $|\mathcal{T}| < m$ **and** $i < n$ **do**
13:   **if** $b_i \leq threshold$ **and** $\frac{\delta_j}{\varepsilon} + threshold \leq u_i(\mathcal{T}) + b_i$ **then**
14:     $\mathcal{T} \leftarrow \mathcal{T} \bigcup \{i\}; p_i \leftarrow threshold$;
15:     $j \leftarrow j + 1; j \leftarrow \min\{j, m/2\}$;
16:   **end if**
17:   $i \leftarrow i + 1$;
18: **end while**

Theorem 1 shows that the proposed TOIM algorithm is truthful and satisfies other desirable properties.

Theorem 1. *TOIM is computationally efficient, individually rational, profitable and truthful.*

Proof. To prove Theorem 1, we show that each property in the theory holds.

Lemma 3. *TOIM is computationally efficient.*

In Algorithm 3, the running time of the two while-loops is $O(n)$. On the other hand, the running time of $SubmodMaxCardinality$ is $O(\frac{1}{\epsilon} n^3 m \log m)$. Thus Algorithm 3 is computationally efficient.

Lemma 4. *TOIM is individually rational.*

Lemma 5. *TOIM is profitable.*

The proofs of Lemmas 4 and 5 are given in the supplementary file, available online.

Lemma 6. *TOIM is truthful.*

Consider user i with cost c_i who arrives at some stage after the cutoff number k, for which the platform is willing to pay $p = threshold$. If by the time the user submits a bid price b_i, the platform has already selected enough qualified users, the user can only get a payment of zero and cannot benefit from reporting a false cost. Otherwise, there is still room to recruit users by the time user i arrives.

If $c_i \leq p$, it won't make any differences by submitting a bid price smaller than p. User i will have utility equalling to $p - c_i \geq 0$ in this case. If the user submits a bid price larger than p, TOIM will reject user i, and thus the user receives a utility of zero.

If $c_i > p$, user i will not be selected by submitting a bid price larger than p. If user i submits a bid smaller than p, she will be selected. However, her utility will be negative, which encourages her to submit a bid reflecting her true cost.

Note that the above arguments also apply to the scenario before the cutoff number k. In summary, TOIM is a truthful online incentive mechanism. □

Although TOIM scarifies platform utility for achieving truthfulness, we next show that it's still $O(\frac{1}{\varepsilon})$-competitive as TBA.

Lemma 7. *TOIM is $O(\frac{1}{\varepsilon})$-competitive.*

Proof. The main arguments are the same as those proposed in the proof of Lemma 2. The difference lies in that TOIM pays a selected user based on a threshold value. At the time of cutoff value, the recruited user set is $\mathcal{T}$, with $|\mathcal{T}| = \lfloor \alpha \cdot m \rfloor$. Denote $\mathcal{T}_c = \mathcal{T}$. For the next selected user i, we have

$$\delta_j/\varepsilon \le u_i(\mathcal{T}) - (threshold - b_i). \tag{6}$$

Denote the user set returned by the offline submodular maximization is $\mathcal{T}'$. Then summing all $m - \lfloor \alpha \cdot m \rfloor$ inequalities gives us

$$\begin{aligned} u(\mathcal{T}')/\varepsilon &\le \sum_{j=1}^{m-\lfloor \alpha \cdot m \rfloor} \delta_j/\varepsilon \\ &\le u(\mathcal{T}) - ((m - \lfloor \alpha \cdot m \rfloor) \cdot threshold - \sum_{i \in \mathcal{T} \setminus \mathcal{T}_c} b_i). \end{aligned} \tag{7}$$

The first inequality comes from the fact that $|\mathcal{T}'| = m/2 \le m - \lfloor \alpha \cdot m \rfloor$, as we assume $\alpha \in [0, 1/2)$. The righthand side of the second inequality represents the actual utility obtained by the platform after the cutoff value. Therefore, combining inequalities (4) and (7) proves that TOIM is $O(\frac{1}{\varepsilon})$-competitive compared with the offline solution. □

3.3 Online Incentives for Arrival-Departure Model

In TBA and TOIM, we assume that users who participate in the bidding process submit bids and leave immediately. We term this setting as zero arrival-departure model, as the users arrive and depart at nearly the same time. The setting is reasonable for the sensing applications where the decision has to be made in time. For example, In LiFS [13], the users receive task description when they enter the target building, and users make immediate bidding profiles hoping the platform to reply shortly, as they may not want to be disturbed anymore when they are working or shopping in that building.

Nevertheless, in other settings, smartphone users may not be in such a hurry, and may stay connected with the platform for some time interval. For example, a user who is staying in a traffic tool or drinking at a coffee shop may play with the platform for some time. In this setting, a user i has a true value tuple (a_i, d_i, c_i), where a_i and d_i ($a_i \le d_i$) are her arrival and departure time, and c_i is the cost as demonstrated above. Therefore, user i will report a bidding profile (a_i', d_i', b_i) to the platform in order to get a payment, with the constraint that $a_i \le a_i' \le d_i' \le d_i$. Here we have assumed that a user cannot report an earlier arrival time and a later departure time. The designed mechanism needs to satisfy the desirable properties as in TOIM. In addition, the truthfulness of the mechanism now includes two aspects: cost-truthfulness and time-truthfulness. In other words, the mechanism should be able to make users report their true arrival and departure time as well as the sensing cost.

Algorithm 4 TOIM-AD

$\mathcal{T} \leftarrow \phi, k = n/2, l = \lfloor \alpha \cdot m \rfloor, r = \lfloor k/e \rfloor, \delta \leftarrow \phi, idx = 1$;
observe first r departed users, forming set $\mathcal{Q}$;
$threshold \leftarrow CalThreshold(\mathcal{Q})$;
$i \leftarrow r + 1, t \leftarrow r$-th user's arrival time;
while $|\mathcal{T}| < m$ **and** $i < n$ **do**
  add users arriving at t to online set $\mathcal{O}$; $\mathcal{O}' \leftarrow \mathcal{O} \setminus \mathcal{T}$;
  while $\mathcal{O}' \ne \phi$ **do**
    $j \leftarrow \arg\max_{j' \in \mathcal{O}'} (u_{j'}(\mathcal{T}) + b_{j'})$;
    if $|\mathcal{T}| < l$ **and** $i \le k$ **and** $b_j \le threshold \le u_j(\mathcal{T}) + b_j$ **then**
      $p_j \leftarrow threshold; \mathcal{T} \leftarrow \mathcal{T} \bigcup \{j\}$;
    else if $i > k$ **and** $b_j \le threshold$ **and** $\frac{\delta_{idx}}{\varepsilon} + threshold \le u_j(\mathcal{T}) + b_j$ **then**
      $p_j \leftarrow threshold; \mathcal{T} \leftarrow \mathcal{T} \bigcup \{j\}$;
      $idx \leftarrow idx + 1; idx \leftarrow \min\{idx, m/2\}$;
    end if
    $i \leftarrow i + 1$;
    if $i == k$ **then**
      $\delta \leftarrow SubmodMaxCardinality(\mathcal{U}(1 : i), m/2, u)$;
    end if
    $\mathcal{O}' \leftarrow \mathcal{O}' \setminus \{j\}$;
  end while
  remove all users departing at t from $\mathcal{O}; t \leftarrow t + 1$;
end while

Algorithm 4 sketches the procedure of the truthful online incentive mechanism for general arrival-departure model (TOIM-AD). As can be seen, the basic logic structure is the same as TOIM. The difference lies in that, at each time step t, there may be several candidate users instead of one as in TOIM. Denote the online set as $\mathcal{O}$, which includes the bidding users who haven't left at t. $\mathcal{T}$ is the set of selected users. Some users may be included into $\mathcal{T}$ before they depart. Therefore, the recruit strategy is to greedily select users from $\mathcal{O}' \leftarrow \mathcal{O} \setminus \mathcal{T}$, who meet the marginal utility constraints. And the selected users are paid the threshold payment when they depart. The desired properties of TOIM-AD are summarized in Theorem 2.

Theorem 2. *TOIM-AD is computationally efficient, individually rational, profitable, truthful.*

Proof. To prove the theorem, it suffices to prove each of the four properties is satisfied. Note that TOIM-AD uses the same recruit conditions and payment scheme as TOIM. Lemmas 4 and 5 have shown that TOIM is individually rational and profitable. Therefore, TOIM-AD is also individually rational and profitable. Considering the computational efficiency, we notice that the only difference of TOIM-AD and TOIM is that at

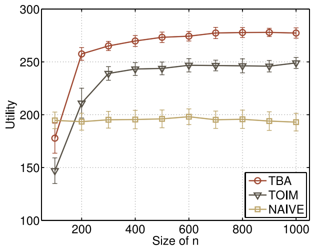

Fig. 2. The effect of n

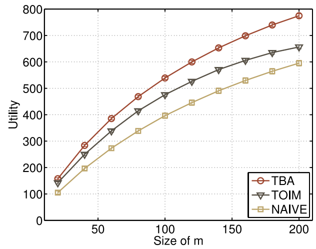

Fig. 3. The effect of m

each time step t, TOIM-AD needs to do $O(n)$ comparisons in the inner while-loop. Therefore the running time of the nested while-loop is $O(n^2)$. Again the computation time is limited by the offline maximization algorithm. Hence TOIM-AD is computationally efficient as TOIM. Based on the above discussion, we only need to prove the following lemma.

Lemma 8. *TOIM-AD is cost-truthful and time-truthful.*

The proof of Lemma 8 is given in the supplementary file of the paper, available online. □

The competitiveness of TOIM-AD is the same as TOIM, as the user selection rules and the marginal utility increment thresholds are constructed in the same manner. Therefore, we can summarize the utility maximization performance of TOIM-AD as the following lemma.

Lemma 9. *TOIM-AD is* $O(\frac{1}{\varepsilon})$*-competitive.*

Remark. The proposed TOIM/TOIM-AD algorithm still works and preserves the above desired properties when different computable submodular utility functions are adopted. Thus TOIM/TOIM-AD can be adapted to diverse applications.

4 Simulations

In this section, we conduct thorough simulations to investigate the performance of the proposed algorithms. Note that TOIM and TOIM-AD have the same expected performance, we only use TOIM in the simulation to compare with TBA. To serve as a baseline, we also design a naive greedy algorithm, i.e., given the random sequence of the applying users, the system determines to accept a bid if the marginal utility is greater than zero, until it has recruited the expected number of users.

In TBA and TOIM, there are three common key parameters: the total number of potential users n, the expected recruitment number of users m, and the approximation ratio ε. We will explore the effect of these parameters respectively.

Simulation setup. The value and cost of each user is uniformly distributed over $[1, 10]$ and $[1, 5]$, respectively. We set three controlled groups of the above parameters as follows:

- set $\mathcal{A} = \{n = [100 : 100 : 1000], m = 40, \alpha = 0.3, \lambda = 800, \varepsilon = 2\}$
- set $\mathcal{B} = \{m = [20 : 20 : 200], n = 2000, \alpha = 0.3, \lambda = 800, \varepsilon = 2\}$
- set $\mathcal{C} = \{\varepsilon = [1.1 : 0.05 : 1.6], n = 2000, m = 40, \alpha = 0.3, \lambda = 500\}$,

where $x = [x_1 : x_2 : x_3]$ means that the value of x is varied from x_1 to x_3 with the increment of x_2. The evaluation for each parameter set is averaged over 100 instances.

4.1 The Effect of n

Parameter set $\mathcal{A}$ is adopted for evaluating the parameter n, which reflects the time restriction of the system. Given that the users are coming around the sensing task area randomly, the system may collect the statistics about the frequency of the occurrence of users. Therefore, if a sensing application has certain time restrictions, the system may predicts the required number of candidate users. Fig. 2 shows that, when the system is expecting to recruit $m = 40$ users, the utility of the system changes according to the total number of candidate users. As can be shown in the figure, when there are more candidate users the proposed TBA and TOIM can choose, the utility of the system increases accordingly. The results are satisfied as the more users there are, the more knowledge our algorithms can get before they make decisions. The curves of the proposed algorithms become flat with the increase of candidate population after $n = 300$. The intuition is that, for a fixed number of expected users, after observing sufficient number of users, the additional observation can help to improve the utility less. On the other hand, The naive algorithm doesn't gain improvements with the increment of the user population at all, as it doesn't learn about the bidding behavior of users and make simple greedy choices.

4.2 The Effect of m

The parameter m is an indication of workload for a specific sensing application. We use parameter set $\mathcal{B}$ to verify the effect of changing m. Fig. 3 depicts that, given a fixed number of candidate users, how the utility will respond to the variation of m. As can be seen from the figure, the marginal increment by recruiting more users is decreasing, which conforms to the expected property of submodular utility objective functions. In other words, for a given number of candidate users, the platform will converge to and reach the maximum utility after recruiting sufficiently large number of users.

4.3 Competitiveness

To investigate the competitiveness of the proposed online mechanisms intuitively, we compare TBA and TOIM with the LSB auction mechanism [16] with parameter set $\mathcal{C}$. LSB approximately maximizes the platform utility in the offline setting and thus is an appropriate upperbound of online mechanisms.

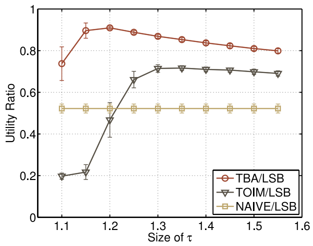

Fig. 4. The effect of ε.

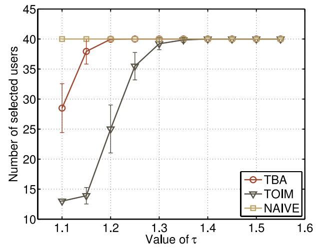

Fig. 5. The effect of ε on recruited user number.

Fig. 4 shows the utility ratios of three online algorithms to LSB with respect to ε. As can be seen from the figure, the curves of TBA/LSB and TOIM/LSB increase with the increment of ε at first, and then they decrease with the increment of ε. The reason is that, when the value of ε is too small, TBA and TOIM tend to aggressively choose the users with utility close to the offline marginal utility increment, which may hardly be met on the course of the algorithms. As a result, insufficient number of users can be recruited in the end (Fig. 5) and the platform utility is thus unsatisfied.

When ε is large enough such that TBA and TOIM are able to recruit the expected number of users, the utility ratios decrease with the increment of ε. The trends of the curves reflect the influence of approximation ratio ε. Also, The highest ratios of TBA/LSB and TOIM/LSB are 90.9 and 71.6 percent, respectively, both of which are much higher than the ratio obtained by the naive greedy algorithm.

5 Related Work

Despite many existing smartphone sensing applications, there are few research works dealing with incentive mechanisms. In [26], Reddy et al. enabled the system to pick well-suited participants for sensing services by developing recruitment frameworks. However, their frameworks are not yet incentive mechanisms as they can only select users, rather than motivate users to participate. Danezis et al. considered motivating users by proposing a sealed-bid second-price auction in [27]. However, they didn't take platform utility into account when designing the auction. Lee and Hoh designed a reverse auction based dynamic price incentive mechanism in [28], where users claim their bid prices at which they are willing to sell the sensed data to the service provider. However, the essential property of truthfulness in mechanism design was not considered. In [29], Duan et al. analyzed and compared different incentive mechanisms that can be used by a client to motivate the collaboration of smartphone users on both data acquisition and distributed computing. Koutsopoulos [30] proposed an incentive mechanism to minimize the total cost of compensating participants, given the quality constraint of sensing tasks, while Zhao et al. [31] tried to maximize the platform value given the cost constraint . In [16], Yang et al. proposed a different model that integrate platform value and cost, and designed two incentive mechanisms from platform-centric and user-centric perspectives. Based on some utility functions, they presented a Stackelberg Game based approach for the platform-centric model and a reverse auction-based incentive mechanism for the user-centric model. Our proposed problem extends their model to the online setting, where we do not assume large amounts of users bidding at the same time. Instead, we accommodate the temporal dynamics of mobile users and design more flexible and efficient mechanisms. On the other hand, the aspect of submodular function maximization of this paper is inspired by [24], where Gupta et al. designed constant-competitive approximation algorithms for non-monotone submodular functions.

Incentive mechanisms are also studied in other networking problems [32], [33], [34], [35], [36]. However, all of these works are tailored to meet the unique characteristics of the studied problems, thus they cannot be applied to the smartphone sensing problem as stated in this work.

6 Conclusion

In this work, we have designed three online incentive mechanisms for smartphone sensing applications based on online reverse auction. TBA intends to approximately maximize the utility of the platform, while TOIM/TOIM-AD makes a tradeoff between maximizing utility and maintaining the essential property of truthfulness. The designed mechanisms are computationally efficient, individually rational for each participant, and profitable for the platform. Also, the mechanisms are highly competitive compared to the optimal solution. Simulation results show the influence of different parameters and good approximation performance compared to the state-of-art offline counterpart. In the future work, we will further explore the competitiveness of the mechanisms. Also, we will investigate more involved incentive mechanisms that can differentiate user quality.

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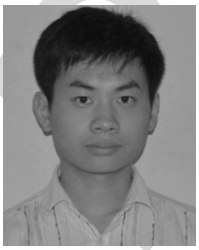
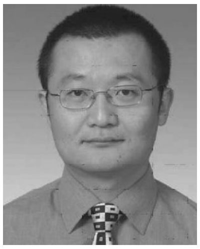
Xinglin Zhang received the BE degree in School of Software from Sun Yat-Sen University, Guangdong, China, in 2010. He is currently working toward the PhD degree in the Department of Computer Science and Engineering, Hong Kong University of Science and Technology. His research interests include wireless ad-hoc/sensor networks, mobile computing and crowdsourcing. He is a Student Member of the IEEE and the ACM.



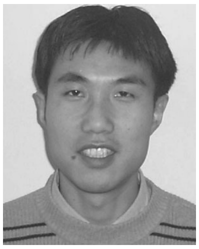
Zheng Yang received the BE degree in computer science from Tsinghua University in 2006 and the PhD degree in computer science from Hong Kong University of Science and Technology in 2010. He is currently an assistant professor in Tsinghua University. His main research interests include wireless ad-hoc/sensor networks and mobile computing. He is a member of the IEEE and the ACM.

Zimu Zhou is currently working toward the PhD degree in the Department of Computer Science and Engineering, Hong Kong University of Science and Technology. He received the BE degree from the Department of Electronic Engineering of Tsinghua University, Beijing, China, in 2011. He is a Student Member of IEEE and ACM.

Haibin Cai received the PhD degree from the Donghua University, Shanghai, China, in 2008, the BEng degree from the National University of Defense Technology in 1997, and the MS degree from the National University of Defense Technology in 2004. He is an associate professor in the Software Engineering Institute, East China Normal University. His research interests include Internet of things, embedded systems and cyber-physical systems.



Lei Chen received the BS degree in computer science and engineering from Tianjin University, China, in 1994, the MA degree from Asian Institute of Technology, Thailand, in 1997, and the PhD degree in computer science from University of Waterloo, Canada, in 2005. He is currently an associate professor in the Department of Computer Science and Engineering at Hong Kong University of Science and Technology. His research interests include crowdsourcing on social networks, uncertain and probabilistic databases, Web data management, multimedia and time series databases, and privacy. He is a member of the IEEE.



Xiang-Yang Li is a professor at the Illinois Institute of Technology. He holds EMC-Endowed Visiting Chair Professorship at Tsinghua University. He currently is distinguished visiting professor at Xi'An JiaoTong University, University of Science and Technology of China, and TongJi University. He is a recipient of China NSF Outstanding Overseas Young Researcher (B). Dr. Li received MS (2000) and PhD (2001) degree at Department of Computer Science from University of Illinois at Urbana-Champaign, a Bachelor degree at Department of Computer Science and a Bachelor degree at Department of Business Management from Tsinghua University, P.R. China, both in 1995. His research interests include mobile computing, cyber physical systems, wireless networks, security and privacy, and algorithms. He is a senior member of IEEE and a member of ACM.

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