Online Quality-Aware Incentive Mechanism for Mobile Crowd Sensing with Extra Bonus

Hui Gao, Chi Harold Liu, *Senior Member, IEEE*, Jian Tang, *Senior Member, IEEE*, Dejun Yang, Pan Hui, *Fellow, IEEE*, and Wendong Wang, *Member, IEEE*

Abstract—Mobile crowd sensing is a new paradigm that enables smart mobile devices to collect and share various types of sensing data in urban environments. However, new challenges arise: one is how to evaluate the quality of data each mobile user potentially is capable of providing; another is how to allocate a satisfactory yet profitable amount of reward to mobile users in order to keep them participating in crowd sensing tasks. In this paper, we first introduce a mathematical model for characterizing quality of sensing data to be contributed by mobile users. Then, we present a utility function and formulate an optimization problem for the platform, who recruits participants to contribute sensing data, to maximize the amount of high quality sensing data under a limited task budget. We next present an effective and quality-aware incentive mechanism to solve this problem for online scenarios where participants may arrive or leave at any random time. Moreover, the proposed incentive mechanism allows the platform to provide selected participants with an extra bonus according to task completion level and their previous performance to motivate them further. We formally show the proposed mechanism has the desirable properties of truthfulness, individual rationality, budgetary feasibility, and computational efficiency. We compare the proposed scheme with existing methods via simulation using a real dataset. Extensive simulation results well justify the effectiveness and robustness of the proposed approach, e.g, compared with another online method "OMG", the gap to the optimum for our proposed Online-QIM approach is reduce by 33.3 percent when budget $B = 1000$.

Index Terms—Mobile crowd sensing, incentive mechanism design, data quality

1 Introduction

With a rich set of embedded sensors and effective computational capabilities, smart mobile devices (e.g., smartphones, wearable devices, etc.) are able to collect and share various types of data in urban environments [1], [2], [3]. This paradigm is called "Mobile Crowd Sensing" [4], [5], [6], which has promising applications in many domains, e.g., transportation, environmental monitoring, health care.

In a mobile crowd sensing campaign, people or entities who need sensing data are called "task publishers", and when they request to collect some types of data, we refer to them as "sensing tasks", or simply "tasks", which usually have multiple requirements. Mobile users who claim their requested rewards to participate in collecting data, and operate sensors of mobile devices physically or subconsciously, are called "participants". Normally, there is also a central "platform" to recruit participants, process sensing data reported by them and send results back to task publishers.

Inevitably, crowd sensing campaigns will involve monetary costs [7], [8], [9], [10]. Thus, it is necessary to introduce an incentive mechanism, which specifies the rewards paid by task publishers to compensate participants' costs and motivate them to contribute sensing data. There are a number of incentive mechanisms that have been proposed. For example, Zhang et al. designed a crowd sensing tournament scheme to maximize the platform's utility, and provided continuous incentives for participants by rewarding them based on the rank achieved [11]. Another challenge is sensing data quality, which, however, has not been well addressed until recently, where Peng et al. proposed a quality-aware incentive mechanism [12], that estimates quality of sensing data, and offers each participant a reward based on his/her effective contribution.

However, most of these works mentioned above mainly consider *offline* scenarios (as shown in Fig. 1), where the concurrent presence of selected participants are required [13], [14]. They assume that all participants will stay from the beginning of all tasks until the end. The platform selects a subset of them to maximize its utility of service (e.g., monetary profit that the platform earns from the received sensing data). However, participants may arrive and leave at any random time, which may not be known in advance; hence, the platform may not always have a sufficient and stable set of participants available for selection. Therefore,

- *H. Gao is with the School of Software Engineering and the State key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications, Beijing 100876, China. E-mail: gaohui786@bupt.edu.cn.*
- *C. H. Liu is with the School of Computer Science and Technology, Beijing Institute of Technology, Beijing 100081, China, and the Department of Computer Information and Security, Sejong University, 209 Neungdong-ro, Gwangjin-gu, Seoul, South Korea. E-mail: liuchi02@gmail.com.*
- *J. Tang is with the Department of Electrical Engineering and Computer Science, Syracuse University, NY 13244. E-mail: jtang02@syr.edu.*
- *D. Yang is with the Department of Computer Science, Colorado School of Mines, Golden, CO 80401. E-mail: djyang@mines.edu.*
- *P. Hui is with the Department of Computer Science and Engineering, Hong Kong University of Science and Technology, Hong Kong, and the Department of Computer Science, University of Helsinki, Helsinki 00014, Finland. E-mail: panhui@cse.ust.hk.*
- *W. Wang is with the State Key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications, Beijing 100876, China. E-mail: wdwang@bupt.edu.cn.*

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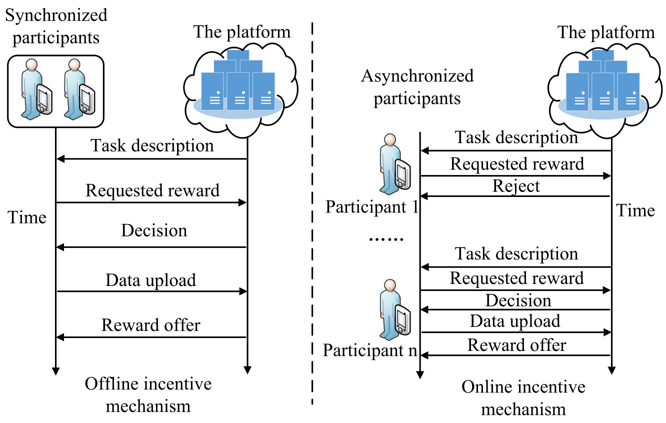


Fig. 1. Offline and online incentive mechanisms for crowd sensing systems.

an online incentive mechanism is needed, based solely on the information of currently available participants, without knowing the future.

The basic workflow of an *online* incentive mechanism is described as follows. First, a task publisher publishes his/her sensing task with certain requirements, such as required data amount and quality, task deadline and budget. Then, the platform automatically divides the sensing region into multiple discrete point-of-interests (PoIs). Meanwhile, the platform selects participants one by one, according to the number of PoIs that are requested to sense, and the remaining task budget. Last, the participant requests a reward before he/she starts to contribute data; and if the platform decides to accept his/her request, after receiving the sensing data, it offers his/her the reward [15]. Finally, the platform processes and sends the sensing data back to the task publisher, either when the task deadline is reached or the budget is exhausted.

Incentive mechanism design has been studied for online scenarios recently. For example, in [16] the authors designed three online incentive mechanisms, namely TBA, TOIM and TOIMAD, based on online reverse auction, which possess the desired properties of computational efficiency, individual rationality, and profitability. Other works of online incentive mechanism designs for mobile crowd sensing include [17], [18]. Even though these are all online mechanisms and most of them have provable nice properties, none of them have carefully addressed quality of sensing data, which is one of most important issues for mobile crowd sensing [19].

Continuously collecting low quality sensing data will undoubtedly do harm to the availability and preciseness of mobile crowd sensing campaigns [13], [20]. It is very challenging to design a quality-aware online incentive mechanism, which has two main challenges:

- Incentive design: it is challenging to consider truthfulness, individual rationality and budget-wise feasibility simultaneously. Here, truthfulness requires the platform to obtain truthful amount of sensing data as a participant has promised. Individual rationality means that a participant should be rewarded no less than his/her sensing cost, and budget-wise feasibility means the total payment does not exceed the total budget. As participants who can strategically determine their level of efforts devoted to a task, which will result in high/low quality sensing, may require appropriate rewards according to their contributions. It is also important that bridge the gap between participant rewards and quality of contributed sensing data.
- Data quality estimation: it is difficult to estimate the quality of sensing data before the platform collects it, since participants might provide low quality sensing data, whether due to malicious intent or malfunctioning devices. As the task publisher needs credible data, if the sensing data, which he/she pays for, is always with low quality and unusable, then the task publisher may decide to quit the crowd sensing systems.

In this paper, we study online incentive mechanism design with careful consideration for quality of sensing data. Based on a data quality model, we propose an effective and provably-good online incentive mechanism for mobile crowd sensing, which takes into account profits of both the platform and participants, and even allows the platform to offer extra bonus to motivate participants further. Specifically, our contributions are summarized in the following:

- We propose a mathematical model for characterizing quality of sensing data to be contributed by participants, which takes into account their reputation.
- We present a utility function and show it is monotone submodular. Based on this function, we formulate an optimization problem, which maximizes the amount of high quality sensing data subject to the task budget.
- We propose an effective and quality-aware online incentive mechanism to solve the problem with consideration for extra bonus.
- We formally show that the proposed incentive mechanism has the desirable properties of truthfulness, individual rationality, budgetary feasibility and computational efficiency.
- We perform extensive simulations on a real dataset to validate the proposed mechanism and justify its superiority by comparing it with existing methods, e.g., for the performance of task accomplishment, the proposed Online-QIM gains 21.7 percent more than that of OMG when budget is 100 units, and the propose mechanism also selects 55 percent more participants. And compared with OMG, the gap between the proposed Online-QIM and optimal method is reduce by 33.3 percent under budget $B = 1000$.

The rest of this paper is organized as follows. We review related work in Section 2. In Section 3, we describe the system model. We present the data quality model and define the utility function Section 4. The proposed online quality-aware incentive mechanism is presented in Section 5. We present and analyze the simulation results in Section 6. The practical issue is discussed in Section 7. Finally, we conclude the paper in Section 8.

2 Related Work

As we mentioned in Section 1, incentive mechanisms have an important role in mobile crowd sensing systems to motivate participants for data contribution while maintaining satisfactory amount of profits for the platform [21], [22], [23], [24], [25]. Beside, high quality data collection methods are also needed to guarantee smooth system operations to provide satisfactory information to the users [14]. In this section, from the above two perspectives we survey the state-of-art of incentive mechanisms and quality-aware mobile crowd sensing systems, and compare that literature with our proposal.

Zheng et al. proposed an incentive mechanism in order to recruit a number of participants to fulfill sensing coverage requirement in interested regions [26]. They employed a monotone greedy approach to allocate tasks, and adopted a proportional share rule based compensation determination scheme to guarantee budget feasibility. Lin et al. designed two frameworks for privacy-preserving, auction-based incentive mechanisms [27], which took into account both the bid privacy of participants and social cost. Xiong et al. introduced a generic incentive allocation framework for two optimal data collection goals: maximized overall spatial-temporal coverage under a predefined incentive budget constraint, and minimized total incentive payment while ensuring predefined coverage [28]. Lin et al. designed two Sybil-proof auction-based incentive mechanisms for mobile crowd sensing [29], in order to prevent Sybil attack where a participant pretended multiple identities to gain benefits. The authors employed three metrics, i.e., running time, total payment, and platform utility, to prove that the proposed mechanisms performed better than that of the compared methods.

From ensuring data quality perspectives, Ding et al. aimed at finding the optimal set of participants who could optimize multiple QoS metrics simultaneously, and satisfy the network resource constraints [30]. They formulated a multi-objective optimization problem that models the participant selection problem. Wang et al. proposed that although the overall utility of multiple tasks is optimized, the sensing quality of individual task might become poor as the number of tasks increased [31]. They re-defined the multi-task allocation problem by introducing a task-specific minimal sensing quality threshold, and employed a descent greedy approach to solve this problem. To deal with low quality data problem, Yang et al. designed an unsupervised learning approach to quantify participants' data qualities and exploited an outlier detection technique to filter out anomalous data items [32]. Furthermore, Guo et al. did their work on measuring and improving the quality of participant contributed visual data, and evaluating the visual quality based on traditional metrics such as resolution [33].

There are also some existing works on quality-aware incentive mechanisms in mobile crowd sensing. Peng et al. proposed an offline incentive mechanism, that incorporated the consideration of data quality into the design of incentive mechanism [13]. It estimated the quality of sensing data, and offered each participant a reward based on his/her effective contribution. Wen et al. proposed an offline incentive mechanism based on a quality-driven auction [14]. To ensure data quality, the platform calculated the probability of a participant's incorrectness of PoI, which was then utilized to find the submitted data with the high reliability. Jin et al. proposed a quality-aware offline incentive mechanism which maximizes social welfare while the quality of collected sensing data must meet the requirement [34]. They formulated the social welfare to a equation which considered selected participants' reward. Pouryazdan et al. studied two existing approaches that quantified sensing data trustworthiness, based on statistical and vote-based participant reputation scores [35]. Also, Jin et al. proposed a quality-aware incentive mechanism which rewarded participant who paid high-effort to sense data [36]. They employed game theory to ensure that all participants would spend their maximum possible effort on sensing.

TABLE 1
List of Important Notations

Notation	Explantation
T, j, $\mathcal{P}$, $\mathcal{P}_m$, d_p	Task deadline, stage of a sensing campaign, set of PoIs, subset of PoIs that participant m can sense and required amount of sensing data in PoI p
B, B_0^j, B_+^j	Budget, basic and bonus part at stage j
$\mathcal{M}$, $\mathcal{M}_s$	Available and selected participants
c_m, c_m^f, c_m^b, c_m'	Requested, forfeit, bonus and actual reward of participant m
w_m, q_m, $\bar{w}$, $\bar{q}$	Willingness and data quality value of participant m, and their averages
r_m^j, $\bar{r}^j$	Reputation value of participant m, and average reputation value at stage j
η_m^j, H, L	Participant strategy at stage j, sensing data effort level
α_j, β_j	Probability of high quality sensing data to be contributed at stage j
$V_m^b(\mathcal{M}_s)$	Marginal utility before picking out high quality data
$V^b(\mathcal{M}_s)$, $V^a(\mathcal{M}_s)$	Utility function before, after picking out high quality data
A^j, $\Delta\rho^j$	Task accomplishment ratio, density threshold at stage j

Different from above existing works, in this paper, we propose an online mechanism where the platform does not have to synchronize large amount of participants simultaneously while distributing tasks. As participants may arrive or leave at any random time, the platform needs to select participants one by one. Furthermore, we also consider data quality, that we leverage participant's reputation value to evaluate their sensing data quality. As a participant's reputation is a long-term and accumulated metric, used to evaluate if he/she is trustable or not, and predict his/her future behaviors.

The frequently used notations are summarized in Table 1

3 System Model

In the beginning, a task publisher publishes his/her sensing task and offers some incentives for those participants who will complete the task. Let the total budget denoted by B, and a set of PoIs in the sensing region be $\mathcal{P} \triangleq \{1, 2, \ldots, P\}$. Each PoI $p \in \mathcal{P}$ has a specific sensing coverage requirement, denoted as d_p, indicating a frequency it should to be sensed. The task is required to be finished before deadline T. Then, as shown in Fig. 2, the platform divides all T into several stages (note that details of how to divide the sensing stages is given in Section 5.2.) Multi-stage process offers participants who are not selected at one stage more opportunities to be selected at the next stage. After that, the platform broadcasts the task, including the sensing region, deadline, etc., to all nearly participants.

Next, we denote a set of available participants who may contribute sensing data by $\mathcal{M} \triangleq \{1, 2, \ldots, M\}$, where M is an unknown parameter. Although data are sensed by sensors mounted in mobile devices, any single participant is the one who decides whether to join a sensing campaign or not, and chooses quality level of sensing data considering his/her privacy protection levels and/or willingness, e.g., to blur location data or delay to contribute data [37]. Therefore, each

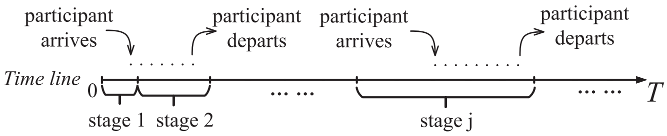


Fig. 2. Considered multiple-stage mobile crowd sensing process.

participant $m \in \mathcal{M}$ is given a reputation value r_m^j at stage j. Each participant m arrives and departs at time $1, 2, \ldots, T$, while his/her arriving time is earlier than his/her departure time. He/She also has a requested reward c_m. Since each participant is moving along a particular trajectory, we assume that he/she can contribute sensing data only at a subset of PoIs, denoted by $\mathcal{P}_m \triangleq \{1, 2, \ldots, P_m\}$, $P_m \leq P$. If selected, his/her final allocated reward (together with extra bonus) is denoted by c_m'.

For participants who agree to join the current sensing campaign, the platform employs following two steps to decide whether or not to select him/her. As shown in Fig. 3, first, it calculates a so-called "marginal utility density" (see Section 4.2 for details) for each arrival participant, as a fraction of a number of PoIs that he/she claims to sense, and his/her requested reward. Then, it selects participants one by one immediately, only if his/her marginal utility density is not less than the pres-set density threshold, while the budget has not been exhausted (see Section 5 for details).

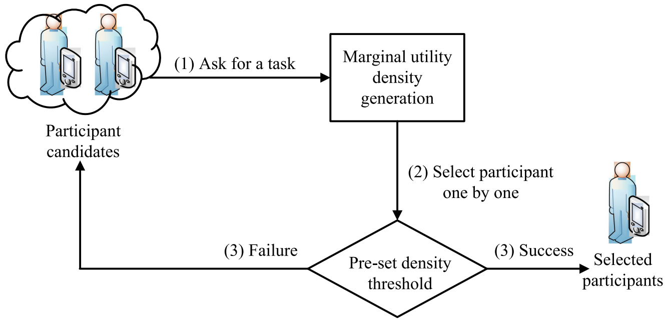


Fig. 3. Participant selection procedure of the proposed incentive mechanism.

4 Data Quality Model and Utility Function

One of challenges many mobile crowd sensing applications need to address is how to measure data quality [12]. In this section, we first present the proposed data quality model. Then, we define the utility function of the platform based on the proposed quality model.

4.1 Data Quality Model

One important factor that affects data quality is the degree of accuracy of sensors, which is mostly determined by sensors' hardware specs. That is, more accurate a sensor is, higher quality of sensing data can be received. Besides, since data are collected by participants who may not receive professional training on how to collect most effective sensing data, also, participants' attitude towards crowdsensing campaigns also differs that may impact the data quality as well. For example, a task wants a participant to contribute GPS coordinates of a location, the participant may contribute wrong coordinates which belongs to another location. For the task that collects photos, quality of sensing data is whether the picture is clear for description. This factor has nothing to do with hardware specs, but highly related to his/her "reputation", which is accumulated from time-being. Therefore, a strategy is needed to guarantee certain degree of data credibility.

4.1.1 Reputation Function and Update Mechanism

A participant' reputation is a long-term and accumulated metric, used to evaluate if he/she is trustable or not, and predict his/her future behaviors. Similar as in [38], we assume that each participant's reputation depends on two metrics, namely, (a) data quality q_m that indicates quality of sensing data contributed by him/her, and (b) each participant's willingness w_m that indicates a participant's enthusiasm for contributing the sensing data. For participant's willingness, as inspired by the social principle [39], the longer a participant is permitted to contribute sensing data, the less he/she contributes to the platform, and the less value of willingness he/she can gain. These two metrics are evaluated and represented by a numeric value in the range of $[0, 1]$, respectively. The participant's reputation feedback function can be defined as $r_m = f(w_m, q_m, \bar{w}, \bar{q})$, where mapping function $f : \mathbb{R}^4 \rightarrow \mathbb{R}$. Here $\overline{w}$ and $\overline{q}$ denote average willingness value and received data quality of all participants, respectively. We will give specific example of f in Section 6.1.

The feedback r_m is in the range of $[-1, 1)$. By definition, its value can infinitely close to 1, and thus we define -1 as definitely negative feedback, 0 as neutral feedback, and 1 as utterly positive feedback. We set the range of feedback based on the consideration that, a participant's feedback value can be hard to be equal to 1, because although one's data contribution seemingly good, there may be another participant whose performance is slightly better than that of him/her. Therefore, we need a function that is approaching 1, but never reaches 1. Compared with positive feedback 1, definitely negative feedback -1 is easier to receive. That is, when a participant does not contribute any sensing data, his/her feedback value is equal to -1. On the other hand, usually people consider that reputation is a long-term and accumulated metric, and good reputation accumulates slowly while bad reputation decreases fast [40].

To update a participant's reputation value, without loss of generality, we use a numeric value in the range of $[0, 1]$ to denote it, from very untrustworthy "0", neutral "0.5" to very trustworthy "1". For every new participant, the platform sets his/her initial value of reputation to neutral (0.5). We next employ a reputation update function, as

$$r_m^j = \frac{1}{\pi} * \arcsin\left(r_m^f\right) + \frac{1}{2}, \tag{1}$$

where $r_m^f = \min\big((r_m^{j-1} + r_m), 1\big)$. And r_m^j, r_m^{j-1} denote the new and most recent reputation value a participant m gains.

4.1.2 High/Low Quality Sensing Estimation by Reputation

As mentioned above, participants may adopt different attitudes and strategies that could lead to different data quality. Here, we utilize the relationship between participant's reputation value and the adopted strategy to estimate quality of data to be contributed. Although a participant with high reputation value may not always contribute high quality sensing data, he/she still has higher probability than the one with relatively lower reputation values. That is, a selected participant can strategically determine his/her level of efforts devoted to a task and adjust this strategy for different tasks. We classify a participant's data contribution as two categories, "High quality sensing", and "Low quality sensing".

Definition 1. *High quality sensing, denoted by $\eta_m^j = H$: For a given stage j, a participant m contributes high quality sensing data q_m which is higher than the average quality of all received data from all participants $\bar{q}$. Otherwise, as Low quality sensing, denoted by $\eta_m^j = L$.*

Since we need to provide satisfactory amount of high quality data with minimum involved participants, without loss of generality, we assume that the platform only needs high quality sensing data. Then, a participant's reputation value is employed to predict his/her determination to perform high quality sensing H before deciding whether to select him/her or not.

Then, we calculate the probability of a participant m to perform high quality sensing data given his/her reputation value, as

$$\Pr\left(\eta_m^{j+1} = H | r_m^j\right) = \begin{cases} \alpha_j, & \text{if } r_m^j \geq \bar{r}^j \\ \beta_j, & \text{if } r_m^j < \bar{r}^j \end{cases}, \tag{2}$$

where $\alpha_j, \beta_j \in [0, 1]$, r_m^j denotes reputation value of a selected participant m at stage j. $\bar{r}^j$ denotes the average reputation value at stage j. The values of α_j and β_j are recalculated at the end of each stage. The details of the update procedure for α_j and β_j will be described later in Algorithm 2.

4.2 Utility Function

4.2.1 Utility Function Definition and Property

Based on (2), we can define the utility function of the platform if selecting a set of participants $\mathcal{M}_s$, as

$$V^b(\mathcal{M}_s) = \sum_{p \in \mathcal{P}} \min\left(d_p, \sum_{m \in \mathcal{M}_s} \mathbb{E}_{m,p}\right), \tag{3}$$

where d_p denotes the required amount of sensing data at PoI p. $\mathbb{E}_{m,p}$ represents that a participant m's expected the amount of high quality sensing data at PoI p, which can be expressed further as $\sum_{p \in \mathcal{P}} \mathbb{E}_{m,p} = P_m * \Pr\left(\eta_m^{j+1} = H | r_m^j\right)$. Then, the overall utility of a task publisher's requirements is represented by $V(\mathcal{D}) = \sum_p \{d_p\}$.

From (3), we know that sensing data that is contributed by different participants may not bring the same utility to the platform, even though they contribute the same amount of sensing data and their reputation values are equal. This is because that, since the platform keeps receiving data, the amount of data that need to be provided by participants decline. Especially, when the platform receives enough amount of sensing data comparable to the task requirement, the utility provided by following participants becomes more and more useless for the platform. Then how to weight utility provided by different participants is a problem. We find that in economics, researchers usually use marginal utility to weight utility of a product, that nicely follows the law of diminishing marginal utility [41]. This theory also applies to mobile crowd sensing campaigns, that since the platform keeps receiving data, the marginal utility provided by following participants becomes more and more useless. The law of diminishing marginal utility can be expressed by a monotone sub-modular function. Next we prove (3) is a monotone sub-modular function.

Lemma 1. *The proposed utility function (3) is a monotone submodular function.*

Proof. Since $V^b(\mathcal{M}_s) = \sum_{p \in \mathcal{P}} \min(d_p, \sum_{m \in \mathcal{M}_s} \mathbb{E}_{m,p})$, for any $\mathcal{M}_{s,1} \subseteq \mathcal{M}_{s,2} \subseteq \mathcal{M}_s$, we have $V^b(\mathcal{M}_{s,1}) \leq V^b(\mathcal{M}_{s,2})$. For any $m' \in \mathcal{M}_s \mathcal{M}_{s,2}$, there is

$$\begin{aligned} & V^b\left(\mathcal{M}_{s,1} \bigcup \{m'\}\right) - V^b\left(\mathcal{M}_{s,1}\right) \\ &= \sum_{p \in \mathcal{P}} \min\left(\max\left(0, d_p - \sum_{m \in \mathcal{M}_{s,1}} \mathbb{E}_{m,p}\right), \mathbb{E}_{m',p}\right) \\ &\geq \sum_{p \in \mathcal{P}} \min\left(\max\left(0, d_p - \sum_{m \in \mathcal{M}_{s,2}} \mathbb{E}_{m,p}\right), \mathbb{E}_{m',p}\right) \\ &= V^b\left(\mathcal{M}_{s,2} \bigcup \{m'\}\right) - V^b(\mathcal{M}_{s,2}). \end{aligned}$$

□

Then, after a set of selected participants $\mathcal{M}_s$ is given, the marginal utility of a participant m can be represented by $V_m^b(\mathcal{M}_s) = V^b(\mathcal{M}_s \bigcup \{m\}) - V^b(\mathcal{M}_s)$.

The theoretical maximal is hard to obtain in a closed-form. Let us consider a special case, that the amount of contributed sensing data follows poisson distribution, with mean λ_p. It is worth noting that our proposed approach has wide applicability for any data arrival process. For a PoI $p \in \mathcal{P}$, let discrete random variable Z_p denote the amount of contributed sensing data, and pr_p denote the probability of high quality sensing data collected at p. Let the discrete random variable Y_p denote the amount of high quality sensing data among all data, then the probability of its amount follows the binomial distribution with parameters Z_p and pr_p. Here we employ Proposition 1 to find out the distribution of the probability of the amount of high quality sensing data.

Proposition 1. *For a PoI $p \in \mathcal{P}$, the probability of the amount of high quality sensing data follows the Poisson distribution with mean $\lambda_p * pr_p$.*

Furthermore, the expectation of the amount of high quality sensing data is computed as $\mathbb{E}(Y_p) = \sum_{y=0}^{\infty} y * \Pr(Y_p = y) = \lambda_p * pr_p$, where

$$\begin{aligned} pr_p &= \Pr(\eta = H, r \geq \bar{r}) + \Pr(\eta = H, r < \bar{r}) \\ &= \alpha * pr' + \beta * (1 - pr'), \end{aligned} \tag{4}$$

and $\alpha = \Pr(\eta = H | r \geq \bar{r})$, $\beta = \Pr(\eta = H | r < \bar{r})$, $pr' = \Pr(r \geq \bar{r})$.

Also, it is agreed that certain relationship may exist between the average reputation value and the probability of performing high quality sensing. This is because that according to the definition of conditional probability function, we know that when the value of $\bar{r}$ is changed, the value of pr' changes accordingly, as well as α and β. Here, we define the relationship between α/β and pr' as a function of g_1 and g_2, respectively, as $\alpha = g_1(pr')$, $\beta = g_2(pr')$, where mapping functions $g_1, g_2 : \mathbb{R} \rightarrow \mathbb{R}$. Detailed choice of specific mapping functions depend of the data used, e.g., they can be either Beta distribution function, linear function, etc. We give a specific example of g_1, g_2 in Section 6.2.

4.2.2 Budget Allocation for Basic and Bonus Parts

Our proposal allows that the selected participants not only earn a "regular" reward based on their contributions, but also may obtain an "extra" bonus to motivate them to contribute more high quality sensing data in future tasks, as long as the overall task budget is not exhausted. To this end, we propose a budget allocation scheme that dynamically allocates reward based on how well previous tasks are completed at former stages.

For each stage j, the total budget is divided into two parts, basic part B_0^j and bonus part B_+^j. The basic part is employed to provide the selected participants reward based on their contributions, while the bonus part is to provide extra bonus based on their reputation values and task completion level. Under certain conditions, if the amount of collected sensing data is not enough, the platform needs to add more basic budget to recruit more participants, while decreasing the bonus allowance. Contrarily, if the amount of collected data is almost enough, the platform will increase the bonus budget to motivate participants to continue joining the sensing campaign for future tasks.

In order to quantify the task completion level, we propose a "task accomplishment ratio", denoted as A^j, in every stage j. We use the Frobenius norm, mathematically used to measure the spatial length of a matrix, to quantify the difference between the required and attained values. Then, A^j is formulated as $A^j = 1 - (||A_r - A_a||_F)/(||A_r||_F)$, where A_r and A_a denote the task accomplishment ratio "requirement" of a task and the actual "attained" value, respectively. We have that $A_r = [d_1, d_2, \ldots, d_P]$ and $A_a = [d_{m,1}, d_{m,2}, \ldots, d_{m,P}]$, where $d_{m,p} = \sum_{m \in \mathcal{M}_s} x_{m,p}$, that $x_{m,p} = 1$ if $p \in \mathcal{P}_m$, and 0 otherwise. Here, we suppose that every selected participant can only contribute one sensing data at one PoI, and then moves to another PoI to collect sensing data as he/she wishes. This assumption can help avoid a participant collecting all of required data at one PoI (which may result in leaving other PoIs unevenly contributed, and current PoI's data not good enough if he/she is not a highly reputable contributor). In other words, we allow more opportunity for other participants to be selected, contributed and rewarded; as a result, data quality can be enhanced as a whole.

We next introduce a budget allocation parameter ε^j, which refers to the percentage of budget serving as the "bonus". For any sensing stage j, $\varepsilon^j = \min(A^{j-1}, \mathrm{const})$, where A^{j-1} is the task accomplishment ratio in previous stage $j-1$, and a constant "const" is a nonnegative decimal fraction. If A^{j-1} is low, i.e., more data needs to be collected at the current stage, we expect to reserve more budget to reward participants and meet their satisfaction, which results in lower ε^j. On the other hand, if A^{j-1} is high, i.e., platform does not have data collection pressure at the current stage, we can reserve more budget as bonus. budget can be more data needs to be collected at the current stage, which results in higher ε^j. In order to achieve this, we set $\mathrm{const} = 0.5$, which means that bonus is at most equals to that the basic part. Details related to how to allocate budget is given in the Step 1 of Section .

5 Proposed Online Quality-aware Incentive Mechanism

In this section, we first formulate the optimization problem, and then we present the proposed incentive mechanism and show it has four nice properties. Given that our approach can be applied for any stage, we omit the stage index j for simplicity in the following.

5.1 Problem Formulation

Since the platform expects to obtain the maximum utility value $V^b(\Delta\mathcal{M}_s)$ from the selected participants' sensing data, under budget B_0 at a stage, where $\Delta\mathcal{M}_s \triangleq \{1, 2, \ldots, \Delta M_s\}$ denotes the set of selected participants at a stage. However, at the end of every stage, the platform will only pick high quality sensing data from all contributed data. Then, the final optimization goal of this paper is defined as

$$\begin{aligned} &\text{maximize: } V^a(\mathcal{M}_s) \\ &\text{subject to: } \sum_{m \in \mathcal{M}_s} c'_m \leq B, \end{aligned} \tag{5}$$

where $V^a(\mathcal{M}_s)$ denotes the utility value if platform chooses only high quality sensing data, defined as

$$V^a(\mathcal{M}_s) = \sum_{p \in \mathcal{P}} \min\left(d_p, \sum_{m \in \mathcal{M}_s} y_{m,p}\right), \tag{6}$$

where $y_{m,p} = 1$, when a PoI $p \in \mathcal{P}_m$ and the platform has completed picking out the high quality sensing data contributed by a participant m; and $y_{m,p} = 0$ otherwise. c'_m denotes a participant m's final reward. Since he/she initially requests c_m, we use $V_m^b(\mathcal{M}_s)/c_m$ to represent his/her marginal utility density, from which we can observe that the greater value of the marginal utility density, the higher utility the platform can obtain from each unit-reward request. Problem (5) is a "set cover" problem, which is NP-hard [42], and therefore in the following descriptions, we use a density threshold $\Delta\rho$ to find its suboptimal solution. We define the "density threshold" as a ratio computed between the number of PoIs and the remaining task budget, which is used to help the platform select participants immediately, indicating the fewest pieces of sensing data a selected participant should contribute per unit reward.

5.2 Proposed Incentive Mechanism

To address the above challenge, we next design our online mechanism. Algorithm 1 shows our proposed "Online Quality-aware Incentive Mechanism (Online-QIM)", mainly used to select participants and allocate reward. Algorithm 2 is the "Threshold Setting Method (TSM)", mainly used to calculate the amount of high quality sensing data and density threshold, serving as the input to Algorithm 1. We describe their main processes as follows.

Step 1 of Online-QIM. In the beginning, the mechanism first separates the budget into the basic part $B_0^j = (1 - \varepsilon^j)B^j$ and bonus part $B_+^j = \varepsilon^j B^j$. Then, the mechanism initializes the value of density threshold and end time of a stage. Here, all time T is divided into $\lfloor \log T \rfloor + 1$ stages, where a stage $j \in \{1, 2, \ldots, \lfloor \log T \rfloor + 1\}$ ends at time $\lfloor 2^{(j-1)} T / 2^{\lfloor \log T \rfloor} \rfloor$. It is worth noting that we use the logarithmic function, since at the very beginning the density threshold may not be set properly, and thus we need to decrease the duration in a few early sensing stages, in order to adjust the density threshold frequently. To this end, with more stages proceed, a more accurate density threshold can be adopted, and thus we gradually decrease the adjustment frequency. Finally, The platform broadcasts the task, including the sensing region, deadline, etc., to all nearly participants.

Step 2 of Online-QIM. It selects participants one by one, as described in Line $5 - 13$. First, all arriving participants are added to a set $\mathcal{M}' \triangleq \{1, 2, \ldots, M'\}$. Then, the participant with higher marginal utility value will be selected first (see Line 7), that if his/her marginal utility density is no less than the value of density threshold, and the budget of this stage is not exhausted, then he/she will be selected (see Line 8). For his/her bonus part, which is designed for rewarding him/her to contribute high quality sensing data for a long time. The more pieces of high quality sensing data he/she has contributed, the higher reputation value he/she gains, and the more bonus he/she can get. If there is enough budget to be paid, then his/her bonus is computed as $c_m^b = (V_m^b(\mathcal{M}_s)/\Delta\rho - c_m)r_m^j$, where $r_m^j \in [0,1]$. On the contrary, his/her bonus is set as $c_m^b = B_+^j$ (see Line 9). The participant m will be removed from $\mathcal{M}'$ after allocating reward to him/her (see Line 12).

Algorithm 1. Online-QIM

Input: Sensing requirement $\mathcal{D}$, stage budget B^j, deadline T
Output: Utility of service value $V^a(\mathcal{M}_s)$
1: $(B_0^j, B_+^j) \leftarrow ((1-\varepsilon^j)B^j, \varepsilon^j B^j)$;
2: $\Delta\rho^j = V(\mathcal{D})/B_0^j$;
3: $(T', t, j, \mathcal{M}_s', \mathcal{M}', \mathcal{M}_s) \leftarrow (\lfloor T/2^{\lfloor \log T \rfloor} \rfloor, 1, 1, \emptyset, \emptyset, \emptyset)$;
4: **while** $t \leq T$ **do**
5: Add all new participants arriving at time t and who are not in set of $\mathcal{M}_s'$ to $\mathcal{M}'$;
6: **while** $M' \neq 0$ **do**
7: $m \leftarrow \arg\max_{m \in \mathcal{M}'}(V_m^b(\mathcal{M}_s))$;
8: **if** $\Delta\rho^j \leq V_m^b(\mathcal{M}_s)/c_m$ and $B_0^j \geq c_m$ **then**
9: $\mathcal{M}_s' \leftarrow m$; $c_m^b = \min((V_m^b(\mathcal{M}_s)/\Delta\rho^j - c_m)r_m^j, B_+^j)$;
10: $c_m' = c_m^b + c_m$; $B_+^j = B_+^j - c_m^b$; $B_0^j = B_0^j - c_m$;
11: **end if**
12: $\mathcal{M}' = \mathcal{M}' \backslash m$;
13: **end while**
14: **if** $t = T'$ **then**
15: $\Delta\mathcal{M}_s = \emptyset$;
16: Remove all participants who depart at time t from $\mathcal{M}_s'$, add them to $\Delta\mathcal{M}_s$;
17: **for** $m \in \Delta M_s$ **do**
18: Calculate the amoung of contributed seinsing data $V_m^{b'}(\mathcal{M}_s)$;
19: **if** $V_m^b(\mathcal{M}_s) > V_m^{b'}(\mathcal{M}_s)$ **then**
20: $c_m^f = c_m * (V_m^b(\mathcal{M}_s) - V_m^{b'}(\mathcal{M}_s))/V_m^b(\mathcal{M}_s)$;
21: $c_m' = c_m - c_m^f$; $B_0^j = B_0^j + c_m^f$; $B_+^j = B_+^j + c_m^b$;
22: **end if**
23: **end for**
24: Add all participants in $\Delta\mathcal{M}_s$ to $\mathcal{M}_s$;
25: $(\Delta\rho^{j+1}, B_0^{j+1}, B_+^{j+1}) \leftarrow \mathbf{T}SM(\Delta\mathcal{M}_s, \mathcal{M}_s, B_0^j + B_+^j)$;
26: $T' = 2T'$;
27: **if** $\Delta\rho^{j+1} == 0$ **then**
28: break;
29: **end if**
30: **end if**
31: $t = t + 1$;
32: **end while**
33: **return** $V^a(\mathcal{M}_s)$

Step 3 of Online-QIM. As one stage finishes (see Line 13), our mechanism first removes all participants to leave from set $\mathcal{M}_s'$, and add them to the selected participant set $\Delta\mathcal{M}_s$. Then, the mechanism checks every participant in set $\Delta\mathcal{M}_s$ that whether the marginal utility equals to what he/she have claimed to contribute or not (see Lines $17-23$). In Line 18, the platform re-calculates his/her marginal utility $V_m^{b'}(\mathcal{M}_s)$. And if the marginal utility contributed by a participant is not equal to what he/she has promised, the mechanism first calculates the percentage gap between the contributed marginal utility and what he/she has promised $(V_m^b(\mathcal{M}_s) - V_m^{b'}(\mathcal{M}_s))/V_m^b(\mathcal{M}_s)$. Then, his/her reward will be re-calculated, which is $c_m' = c_m - c_m^f$, where c_m^f denotes the forfeit from the amount of sensing data he/she does not eventually contribute. The forfeit and bonus reward will be recovered, which will be added to the budget in Line 21.

Algorithm 2. TSM

Input: Select participants a stage $\Delta\mathcal{M}_s$, total select participants $\mathcal{M}_s$, stage budget B^j
Output: Density threshold $\Delta\rho^{j+1}$, budget B_0^{j+1} and B_+^{j+1}
1: $\bar{q} = \sum_{m \in \mathcal{M}_s} q_m / M_s$;
2: $A^j = 1 - ||A_r - A_a||_F / ||A_r||_F$; $\varepsilon^{j+1} = \min(A^j, \text{const})$;
3: $(B_+^{j+1}, B_0^{j+1}, u\_\text{num}) \leftarrow (\varepsilon^{j+1}B^j, (1-\varepsilon^{j+1})B^j, 0)$;
4: **for** $m = 1 \rightarrow \Delta M_s$ **do**
5: $\alpha\_\text{num} = 0$; $\beta\_\text{num} = 0$; $p = 1$;
6: **if** $r_m^j \geq \bar{r}^j$ **then**
7: $u\_\text{num} = u\_\text{num} + 1$;
8: **while** $p <= P_m$ **do**
9: **if** $q_m \geq \bar{q}$ **then**
10: $\alpha\_\text{num} = \alpha\_\text{num} + 1$;
11: **end if**
12: $p = p + 1$;
13: **end while**
14: $\alpha_m = \alpha\_\text{num}/P_m$;
15: **else**
16: **while** $p <= P_m$ **do**
17: **if** $q_m \geq \bar{q}$ **then**
18: $\beta\_\text{num} = \beta\_\text{num} + 1$;
19: **end if**
20: $p = p + 1$;
21: **end while**
22: $\beta_m = \beta\_\text{num}/P_m$;
23: **end if**
24: $r_m^{j+1} = \frac{1}{\pi}\arctan(\text{const} * (r_m^j + r_m^f))$;
25: **end for**
26: $\bar{r}^{j+1} = \sum_{m \in \Delta\mathcal{M}_s} r_m^{j+1} / \Delta M_s$;
27: $k = [V^a(\Delta\mathcal{M}_s) - V^b(\Delta\mathcal{M}_s)] / \sum_{m \in \Delta\mathcal{M}_s} c_m'$;
28: $\delta^j = g^k$; $\alpha^j = \sum \alpha_m / u\_\text{num}$; $\beta^j = \sum \beta_m / (\Delta M_s - u\_\text{num})$;
29: $\Delta\rho^{j+1} = \delta^j((V(\mathcal{D}) - V^a(\mathcal{M}_s))/B_0^{j+1})$;
30: **return** $\Delta\rho^{j+1}$, B_0^{j+1}, B_+^{j+1}

Step 4 of Online-QIM. It computes a new density threshold $\Delta\rho^{j+1}$, basic part B_0^{j+1} and bonus part B_+^{j+1}, according to Algorithm 2. The results will be used for making decisions at the next stage. Finally, our mechanism either continues to select participants at the next stage or finishes the task, depending on the task deadline or the remaining budget.

We next introduce Algorithm 2, whose main process is as follows.

Step 1 of TSM. It first calculates the task accomplishment ratio A and then obtains the parameter ε^j (see Line 2). Then, it divides the total budget into two parts (see Line 3).

Step 2 of TSM. It calculates the amount of high quality sensing data and update the reputation value of every selected participant (see Line $4-25$). Then, it calculates the average gap δ between the predicted and actual obtained marginal value α and β (see Line $27-28$). Here, $g > 1$ determines the new gap in one stage. That is, if the prediction equals to the actual value, or the platform has received enough data, then the utility density threshold does not need to be underestimated in the next stage, where $\delta = 1$; otherwise, the density threshold needs to be slightly underestimated, i.e., $\delta < 1$, for guaranteeing enough participants to be selected and avoiding the waste of task budget.

Step 3 of TSM. The rest of Algorithm 2 is used to calculate the new threshold $\Delta\rho^{j+1}$ and return with two parts of budget, served as the inputs to Algorithm 1.

5.3 Four Desired Properties

In the following, we analyze our proposed mechanism by introducing four desirable properties, which has nothing to do with any special use case or data. In general, these properties are sufficient for designing a good incentive mechanism for mobile crowd sensing. Truthfulness requires the platform to obtain truthful amount of sensing data as a participant has promised. Individual rationality means that a participant should be rewarded no less than his/her sensing cost, and budget-wise feasibility means the total payment does not exceed the total budget. Computational efficiency ensures the proposed incentive mechanism can run in real time.

Proposition 2. *The proposed Online-QIM is truthful.*

Here we employ the knowledge of Game Theory to analyze Proposition 2. We assume that the participants are rational but selfish, that they do not contribute more sensing data than what they have claimed. To this end, we consider two strategies a participant m can adopt, as:

- Strategy S1: he/she contributes equal amount of sensing data as he/she claims.
- Strategy S2: he/she contributes less amount of sensing data as he/she claims.

Proof. Let the final reward a participant m earns denoted by $c'_m(S1)$ for employing S1 and $c'_m(S2)$ for employing S2, respectively. In Table 2 we analyze not only the final reward a participant m earns at this stage, but also two possible conditions in next stage when he/she participates again after he/she adopts different strategies. Here "future condition 1 (FC 1)" represents that participant m will be selected after adopting either of strategies, and "future condition 2 (FC 2)" represents that participant m will be selected if he/she adopts S1. There is no probability that m will be selected if he/she adopts the S2. This is because that, $r_m(S1) > r_m(S2)$, which causes $V^b_{m,1}(\mathcal{M}_s) \geq V^b_{m,2}(\mathcal{M}_s)$, where $V^b_{m,1}(\mathcal{M}_s)$ denotes the marginal utility of participant m after adopting S1 and $V^b_{m,2}(\mathcal{M}_s)$ denotes his/her marginal utility after adopting S2. Based on Algorithm 1, we know that if m can be selected after adopting S2, he/she definitely can be selected after adopting of S1.

For those data participant m does not contribute as he/she claimed, forfeit is denoted as c^f_m, and bonus is denoted as $c^b_m(S1)$ and $c^b_m(S2)$, respectively. From (7), we know that if $r_m(S1) > r_m(S2)$, then

$$\left(\frac{V^b_m(\mathcal{M}_s)}{\Delta\rho} - c_m\right) * r_m(S1) > \left(\frac{V^b_m(\mathcal{M}_s)}{\Delta\rho} - c_m\right) * r_m(S2).$$

Also, $c^b_m(S1) \geq c^b_m(S2)$. Based on the above analysis, we summarize that $c'_m(S1) \geq c'_m(S2)$, i.e., S1 is optimal as it can earn the maximum reward for a participant m. Then, the platform can receive the actual amount of sensing data. It is worth noting that, for ease of exposition, we do not consider that m will employ S2 again in the future. However, it is easy to find out that, since the forfeit c^f_m exists, the participant only employs S1 in order to earn more reward. Furthermore, a participant's reputation is a long-term and accumulated metric. That is, negative effect will still make impact in future stages, after the participant employs S2, i.e., he/she always earns no more reward than employing S1. □

TABLE 2
Final Reward a Participant m Earned

Strategy	Current stage	FC 1	FC 2
S1	$c_m + c^b_m(S1)$	$c_m + c^b_m(S1)$	$c_m + c^b_m(S1)$
S2	$c_m - c^f_m$	$c_m + c^b_m(S2)$	0

Proposition 3. *The proposed Online-QIM is individually rational.*

Proof. Any selected participant m can earn reward $c'_m = c^b_m + c_m$, where

$$c^b_m = \min\left(\left(V^b_m(\mathcal{M}_s)/\Delta\rho - c_m\right) * r_m, B_+\right). \tag{7}$$

Note that $c^b_m \geq 0$ always holds. Therefore, $c'_m \geq c_m$, which proves that the selected participant m earns no less than his/her requested reward. □

Proposition 4. *The proposed Online-QIM is budget-wise feasible.*

Proof. At each stage $j \in [1, \lfloor \log T \rfloor + 1]$, our mechanism uses a stage-budget B_0 and B_+. From Lines $7-9$ in Algorithm 1, it is guaranteed that the current total payment does not exceed the stage-budget B_0 and B_+. Therefore, every stage is budget-wise feasible, and when the deadline T arrives, the total payment does not exceed the total budget B. □

Proposition 5. *The proposed Online-QIM is computationally efficient.*

Proof. We focus on the computation complexity at each stage, as the proposed Online-QIM runs at real-time. Since the mechanism takes $\mathcal{O}(P_m)$ time to compute the marginal value of each participant m, it grows to $\mathcal{O}(P)$ in the worst condition. Based on that, the running time of computing the allocations and payments at each stage is bounded by $\mathcal{O}(M'P) < \mathcal{O}(MP)$ (see Line 5-12 in Algorithm 1). Next, our mechanism checks the amount of sensing data contributed by the selected participants, which takes $\mathcal{O}(\Delta M_s P)$ time. As we know that $\Delta\mathcal{M}_s \subset \mathcal{M}'_s$, which refers to the worst condition, all participants leave before the stage, also takes $\mathcal{O}(M'P)$ (see Line 16-20 in Algorithm 1). Next, we analyze the complexity of computing the Algorithm 2, the running time of which is bounded by $\mathcal{O}(M'P)$ in the worse case. Therefore, the computational complexity at each stage is bounded by $\mathcal{O}(MP)$. □

6 Performance Evaluation

In this section, we first introduce simulation setup (including the real dataset used for experiments), and then present and analyze the simulation results.

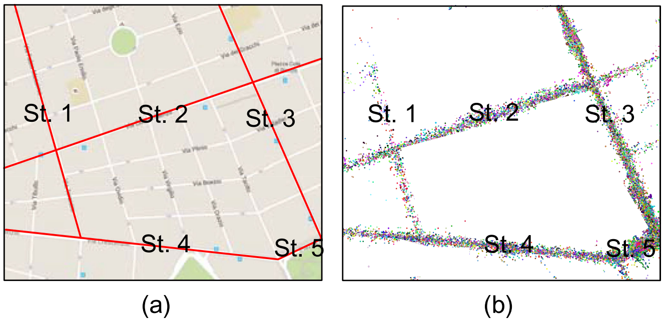


Fig. 4. Data set of taxi mobility trace in Rome, Italy, where (a) shows the sensing region (five streets) colored in red and (b) shows the GPS points inside the region.

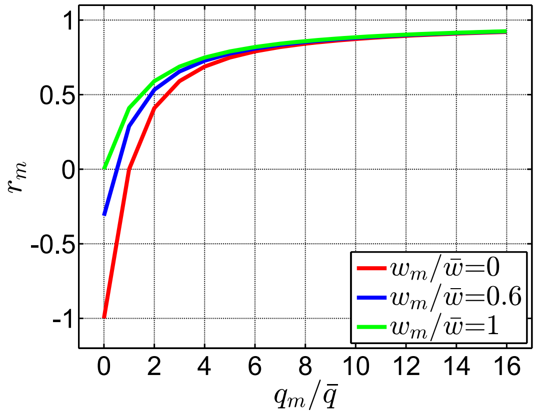


Fig. 5. Participant's reputation feedback value as a function of $q_m/\bar{q}$ when varying $w_m/\bar{w}$.

6.1 Setup

We employ the dataset of taxi mobility traces in Rome, Italy as the participants' trajectories in a mobile crowd sensing campaign, where GPS coordinates of approximately 320 taxis are recorded over 30 consecutive days [43]. Each trajectory is marked by a sequence of time-stamped GPS points that contain taxi driver ID, time stamp (date and time), and taxi drivers' position (latitude and longitude). We use map offset correction data as "data quality" in our experiment, which is employed to evaluate participant's marginal utility that is mentioned in Section 4. Map offset is a value that indicates the value gap between GPS coordinates in real world (i.e., accurate values) and those in a digital map. We adopt the following procedures to set up our simulation platform:

- As all traces are recorded in different parts of Rome. We find a region about 800×500 m^2 and choose 5 busy streets to be the sensing region that are colored in red (see Fig. 4a). Fig. 4b shows the GPS points inside the region.
- All the 1040 traces in the considered region (see Fig. 4) are recorded from 67 potential (candidate) participants, i.e., $M = 67$. Since these traces are recorded at different days, in our simulation we overlay them into one day. The length of these traces are different, but most of them are from 50 to 200 m.
- We explicitly consider a road sensing application, and each road is further divided into discrete PoIs with a uniform spacing of 1m, so that all roads consist of 2,582 PoIs in total. We let the coverage requirement of each PoI be 2. We set the deadline (T) to be 86,400 seconds (i.e., one day). According the dividing method, we can calculate that $\lfloor \log 86400 \rfloor + 1 = 17$, then there are 17 sensing stages in total. Since a participant's incentive requirement can be realized in different forms in practice, such as real money or bonus points, we use dimensionless units to represent both the participants' incentive requests and task budget. Budget is varied from 100 to 1,000 units with the increment of 100 units. The requested reward of participants is set as a uniformly distributed random variable from 1 to 10 units. We set $g = 1.1$ in the gap value function that is shown in Line 27 of Algorithm 2.
- We employ the map offset values to indicate a participant's sensing data quality, which is denoted by $q_m, \forall m \in \mathcal{M}$. The map offset of use are nonlinear, in the range of $[300, 500]$ miles. We collect those in the same latitude into a set. At the start of the simulation, we set the probability values of performing high quality sensing $\alpha = \beta = 0.5$.
- In this paper, we give a specific formulation of mapping function f in Section 3, as $r_m = \frac{4}{\pi} * \arctan\left(\frac{1}{2} * \left(w_m/\overline{w} + q_m/\overline{q}\right)\right) - 1$, where $\overline{w}$ and $\overline{q}$ denotes average willingness value and received data quality of all participants, respectively. We employ the division form, as a ratio, $w_m/\overline{w}$ and $q_m/\overline{q}$ to show how well (or badly) this participant performs, if compared with others. As we mentioned in Section 4.1, the feedback r_m is in the range of $[-1, 1)$. By definition, its value can infinitely close to 1, and thus we define -1 as definitely negative feedback, 0 as neutral feedback, and 1 as utterly positive feedback. Fig. 5 shows the curve of feedback value as a function of $q_m/\bar{q}$ for different $w_m/\bar{w} = 0$, $w_m/\bar{w} = 0.6$ and $w_m/\bar{w} = 1$, respectively. The shape of curve captures the mentioned property by increasing fast from -1 to 0, and then slowly from 0 to 1. Meanwhile, higher willingness (i.e., higher ratio of $w_m/\overline{w}$) will receive higher reputation values given the same $q_m/\overline{q}$.

To evaluate the performance of our proposed mechanism (referred as "Online-QIM"), three other approaches are implemented and compared.

- "Online Mechanism under General Case" as proposed in [18] (referred as "OMG"), which is also an online incentive mechanism that designs a threshold at the end of every stage to help the platform to select participants. The OMG is done based on the former work [16], which, as the authors said, is the first work on online mechanism design for crowd sensing applications. Different from our proposal, OMG employs a greedy strategy to compute the density threshold. At the end of every stage, the platform re-arranges every selected participant based on his/her contributed marginal density value from high to low, and selects a set of participants that can provide the greatest value of utility, until the budget of current stage runs out. The result is used as the density threshold of next stage.
- The second compared approach adopts the same strategy as "OMG", but decides the value of $\Delta\rho$ randomly at every stage (referred as "OMG (random)").
- The third compared approach is that the platform uses a fixed value of $\Delta\rho$ to select participants (referred as "Fixed"). In order to collect enough sensing data

under the limited budget, we use the ratio of requested amount of sensing data and budget to be calculate this fixed value, i.e., $\Delta\rho = \Sigma_{p\in\mathcal{P}} d_p/B$.

6.2 Analysis of Maximum Utility Value

In Section 4.2, we used general mapping functions g_1 and g_2 to represent the relationship between pr' and α, β. Here we express their relationship by plotting the real dataset, as shown in Fig. 6, where a clear linear relationship is observed (with 95 percent confidence interval) for both g_1, g_2, and thus we can re-write them as $\alpha = f_1 * pr'$ and $\beta = f_2 * pr'$, where let f_1 and f_2 denote slope. Note that for simplicity reasons, we omit the interceptions as constant factors. Therefore, (4) can be rewritten as

$$pr_p = f_1 pr'^2 + f_2 pr'(1 - pr') = (f_1 - f_2)pr'^2 + f_2 pr'. \tag{8}$$

Based on this, we compute the maximum of $V^b(\mathcal{M}_s)$ as

$$\max V^b(\mathcal{M}_s) = \begin{cases} \sum_{p\in\mathcal{P}} \min\left(d_p, \frac{\lambda_p f_2^2}{4(f_2-f_1)}\right), & \text{if } f_1 \neq f_2 \\ \sum_{p\in\mathcal{P}} \min\left(d_p, \lambda_p f_2\right), & \text{if } f_1 = f_2. \end{cases} \tag{9}$$

Proof. To maximize pr (here we omit subscript "p" for convenience), taking a derivative of (8) with respect to pr', we have $\partial pr/\partial pr' = 2 * (f_1 - f_2) * pr' + f_2$.

We first discuss the condition $f_1 \neq f_2$, while the other condition will be discussed later. After setting $\partial pr/\partial pr' = 0$, we have $pr' = f_2/\left(2 * (f_2 - f_1)\right)$. We take derivative $\partial pr/\partial pr'$ to testify whether pr' is the maximum value or not, as $\partial^2 pr/\partial pr'^2 = 2 * (f_1 - f_2)$. Since $pr' \geq 0$, $f_1 > 0$ and $f_2 > 0$, we have $f_1 < f_2$, and $\partial^2 pr/\partial pr'^2 < 0$. Then, we know that pr is the maximum value, since $pr = f_2^2/\left(4 * (f_2 - f_1)\right)$. Then, the maximum value of $V^b(\mathcal{M}_s)$ is computed as

$$\max V^b(\mathcal{M}_s) = \sum_{p\in\mathcal{P}} \min\left(d_p, \frac{\lambda_p * f_2^2}{4 * (f_2 - f_1)}\right), f_1 \neq f_2. \tag{10}$$

We next discuss the condition $f_1 = f_2$. $\partial pr/\partial pr'$ can be rewritten as $\partial pr/\partial pr' = f_2 > 0$, which means (8) is a monotonically increasing function and the maximum value of (8) is given when $pr' = 1$. Then, the maximum of $V^b(\mathcal{S})$ is computed as

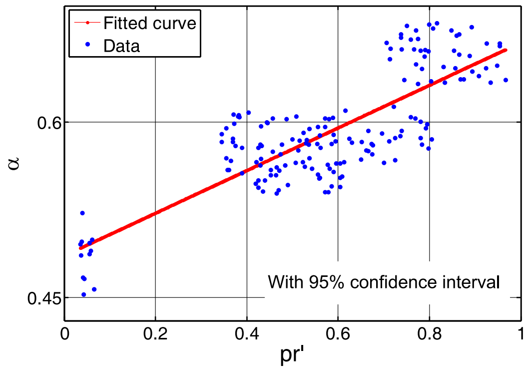
$$\max V^b(\mathcal{M}_s) = \sum_{p\in\mathcal{P}} \min\left(d_p, \lambda_p * f_2\right), f_1 = f_2. \tag{11}$$

□

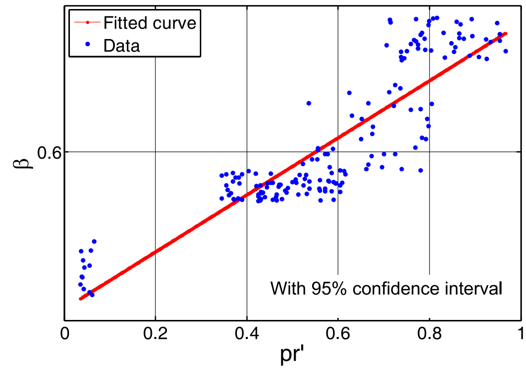
6.3 Results and Analysis

We present the simulation results in Figs. 7, 8, 9, and 10. It is worth noting that for each data point in these figures, we performed 1,000 runs and took the average.

To further investigate whether the proposed mechanism considers the participant's profit, our approach allows an "extra" bonus to be provided to the selected participants. As shown in Fig. 7a, the total reward that allocates to all selected participants are more than what they have requested. Specifically, zoom-in figure of Fig. 7a also shows the requested and final paid reward when $B = 200$ and 1,000 units, respectively. Fig. 7b shows the change of total reputation value of all selected participants with respect to different budget, where we observe that with the increase of more budget, the platform is able to recruit more reputable participants to contribute data. To better understand the change of reputation value over stages, we randomly pick up five participants (with ID 11, 17, 23, 45 and 61) and show their reputation update processes as shown in Fig. 7c, when budget is 1,000 units. We observe that Participant 45 contributed one piece of sensing data during Stage 11, but unfortunately of low quality. Correspondingly, his/her reputation value is decreased. Participant 17 contributed also one piece of data, but of high quality during Stage 9, and thus his/her reputation value is increased after. This change demonstrates the ability of our reputation module to dynamically adjust the reputation scores as a reflection of participant behavioral changes. We use Table 3 to verify Proposition 2, where we observe that the values of reward and reputation of strategy S1 are greater than that of strategy S2. In other words, if the selected participant aims to gain more reward, he/she has to contribute the claimed quantity of sensing data. If so, the platform can receive enough amount of sensing data, which guarantees the platform's profit.



(a)



(b)

Fig. 6. Fitting mapping functions g_1 and g_2, based on used dataset: (a) $\alpha = g_1(pr')$ and (b) $\beta = g_2(pr')$.

Fig. 8a shows the change of utility values $V^b(M_s)$ *before* picking high quality data, and $V^a(M_s)$ *after* picking high quality data by three different methods under different budget constraints. Besides, we also calculate the maximum of $V^b(M_s)$ according to (9). As described in Section 5.1, the platform only picks high quality sensing data from all contributed data at the end of every stage; in other words, some pieces of low quality data are not counted in the value of $V^a(M_s)$, which causes the value of $V^b(M_s)$ higher than that of $V^a(M_s)$. We also observe that our proposed Online-QIM always obtains the highest value. For example, $V^b(M_s) = 2623$ by Online-QIM when budget $B = 100$ units, and as the budget increases to $B = 1{,}000$ units, $V^b(M_s) = 4334$. For the utility values $V^a(M_s)$, it is observed that Online-QIM is also always better. Its lowest and highest values reach 1328, 2379, when $B = 100$, 1000 units, respectively. In order to

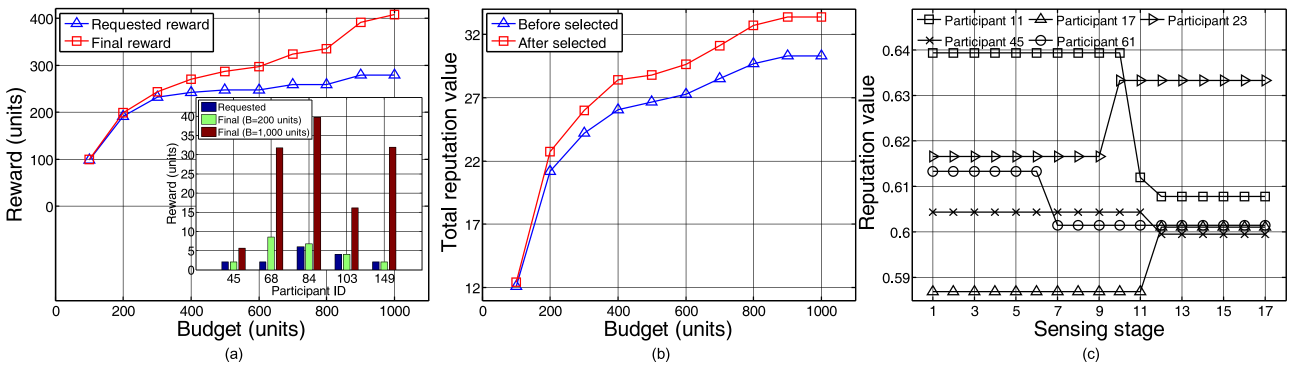


Fig. 7. (a) shows the reward earned by selected participants, compared with their requested one under different budget. (b) shows the change of total reputation value of all selected participants with respect to different budget. (c) shows a zoom-in view of five participants of (b) over different stages when budget is 1,000 units.

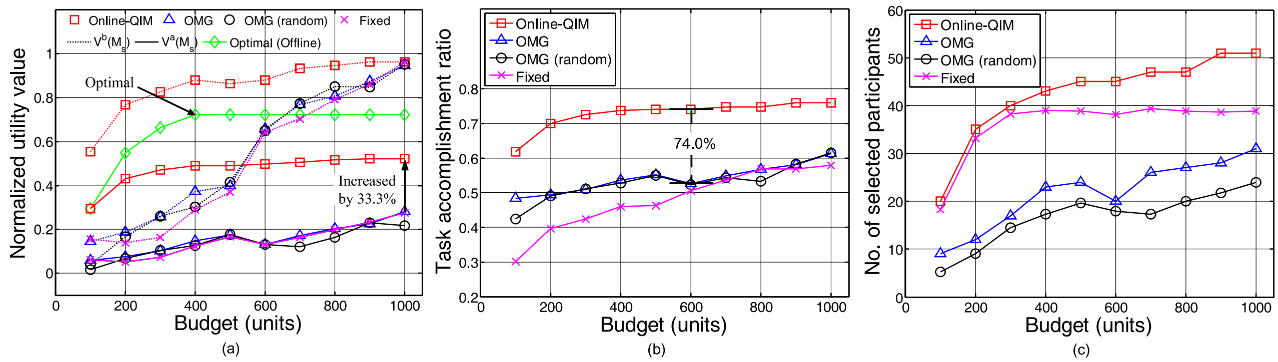


Fig. 8. (a)-(c) show the normalized utility value received, task accomplishment ratio, and no. of selected participants by four compared approaches under various budget, respectively.

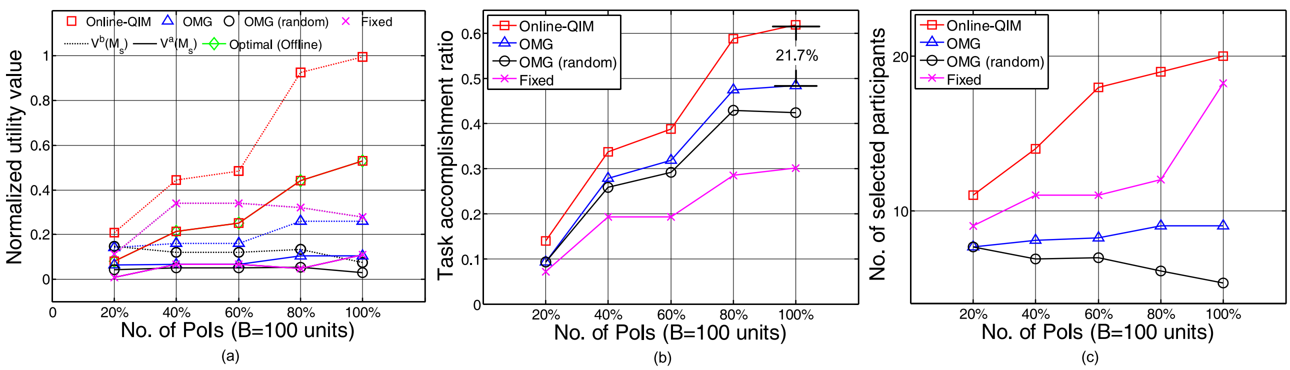


Fig. 9. (a)-(c) show the normalized utility value received, task accomplishment ratio, and no. of selected participants by four compared approaches under the setting of different proportion of available PoIs.

understand how close our solution approximates the optimum, we perform exhaustive search to find the optimal results in the offline scenario, where the true types or strategies of all participants are known *a priori*. As shown in Fig. 8a, compared with OMG (diamond or circle lines), the gap between the proposed Online-QIM solution (square lines) and optimal solution (diamond line) is significantly reduced (e.g., by 33.3 percent, when budget $B = 1000$). This verifies that the proposed scheme fully considers the platform's profit, more than two other comparisons. Besides, Fig. 8b shows the performance of task accomplishment ratio. Our proposed Online-QIM is still better than others, i.e., it achieves highest satisfactory level of collected sensing data, corresponding to the task requirement. We see that Online-QIM gains 74.0 percent more than that of OMG and OMG (random) methods, when $B = 600$ units. As mentioned earlier that our scheme selects participants as many as possible under the budget constraint, in order to allow more participants to earn reward as a return. This is verified in Fig. 8c, where our proposal selects more participants than others.

TABLE 3
Different Reward and Reputation Values after the Selected Participant Chooses Different Strategies

ID (m)	11	17	23	45	61
S1 reward	2.00	10.00	2.70	8.00	4.00
S2 reward	0.02	0.11	1.43	0.13	0.07
S1 reputation	0.608	0.601	0.633	0.600	0.602
S2 reputation	0.434	0.445	0.443	0.434	0.436

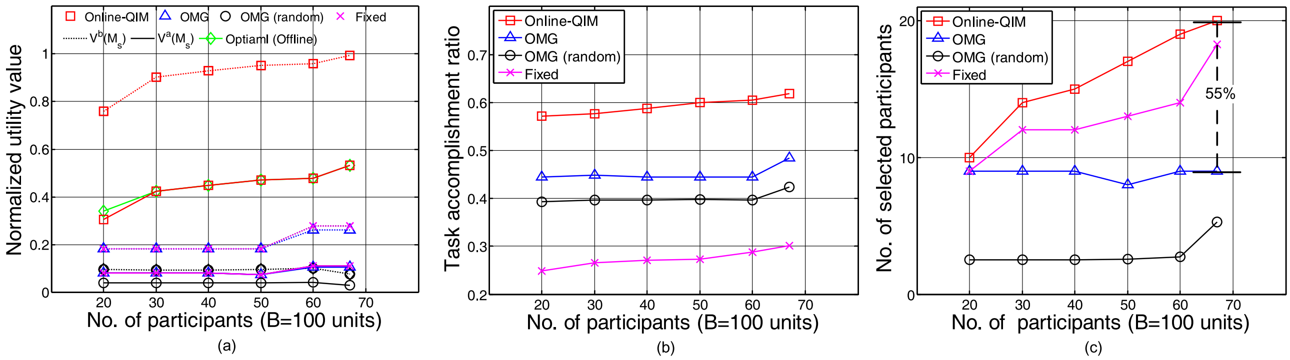


Fig. 10. (a)-(c) show the normalized utility value received, task accomplishment ratio, and no. of selected participants by four compared methods under the setting of different amount of available participants.

TABLE 4
Utility Change When Different Reputation is Considered

Budget		100	200	300	400	500	600	700	800	900	1,000
$r \in (0, 0.3)$	$V^b(M_s)$	2325.5	2886.4	3068.2	4229.1	4229.1	4259.1	4283.8	4501.5	4763.1	4808.3
	$V^a(M_s)$	545	862	867	975	975	958	994	999	1050	1053
$r \in (0.7, 1)$	$V^b(M_s)$	2623.2	4045.3	4341.9	4462.4	4394.8	4455.9	4810.7	4844.3	4899.1	5003.0
	$V^a(M_s)$	1,328	1,937	2,118	2,203	2,208	2,237	2,305	2,319	2,379	2,400

Figs. 9a, 9b, and 9c show the normalized utility value, task accomplishment ratio, no. of selected participants by four compared approaches under the setting of $20\%, 40\%, \ldots, 100\%$ of available PoIs. From Fig. 9a we observe that the proposed Online-QIM always obtains the highest value. It best approximates the optimal solution among all four methods. For example, $V^b(M_s) = 526$ by Online-QIM when there are 20 percent of available PoIs, and when this ratio increases to 100 percent (all PoIs), $V^b(M_s) = 2623$ by our method. For the utility value $V^a(M_s)$, it is observed that Online-QIM is also always better than the others. Its lowest and highest values reach 199, 1328, respectively. Besides, our solution is closest to the maximum $V^b(M_s)$ which is calculated by (9). Fig. 9b shows the obtained task accomplishment ratio. Our proposal is still better than others, i.e., it achieves highest satisfactory level of collected sensing data, corresponding to the task requirement. We observe that Online-QIM gains 21.7 percent more than that of OMG and OMG (random) methods, when considering all available PoIs. Similarly, Fig. 9c shows that our proposal selects more participants than others.

Figs. 10a, 10b, and 10c show the normalized utility value, task accomplishment ratio, no. of selected participants by four compared approaches under the setting of different available participants. The same observation has been made that Online-QIM best approximates the optimal solution among all four methods. We observe that the proposed method achieves utility $V^b(M_s) = 1895$ and $V^b(M_s) = 2487$ when the number of available participants $\mathcal{M} = 20$ and $\mathcal{M} = 67$, respectively. For the utility values $V^a(M_s)$, its lowest and highest values reach $761, 1328$, when the number of available participants $\mathcal{M} = 20, 67$, respectively. Besides, our method also selects the most amount of participants, as shown in Fig. 10c. We see that Online-QIM selects 55 percent more participants than that of OMG method.

In order to investigate how the system deals with the low quality sensing data contributed by low reputation participants, we show the attained utility values under different budgets $B = 100, 200, \ldots, 1000$, as in Table 4. Parameter $r \in (0, 0.3)$ refers to the case where relatively low reputation participants contribute data, and $r \in (0, 0.3)$ refers to high reputation participants otherwise. We can see that although the initially collected amount of data, represented by $V^b(M_s)$ for two different ranges of r are of the same scale, our proposal successfully picks out only high quality data, as represented by $V^a(M_s)$, resulting in a much lower $V^a(M_s)$ (when $r \in (0, 0.3)$).

Compared with OMG approach, since we use different methods to calculate density threshold, Online-QIM performs better. This is because that OMG employs a greedy strategy and sets a fixed high density threshold, that to certain extend it refuses considerable number of participants to contribute sensing data. Nevertheless, Online-QIM considers the data amount received at current stage as well as the remaining budget, then it calculates the density threshold of the next stage. This is further confirmed by Figs. 8c, 9c and 10c, where we observe that OMG selects fewer participants than Online-QIM, that further results in lower utility.

7 Practical Issue Related to Participant's Requested Reward

In this paper, we use the requested reward as the input to our algorithm. In practice, it is based on a user's cost, and ensuring that users will report their cost truthfully is important. There are some existing methods to decide the amount of participant's requested reward for mobile crowd sensing systems. For example, Jin et al. let participants set reward by their own, then the platform decides whether to accept the requested reward or not [44]. Peng et. al. also allowed the participants set the reward first, then the platform will give each of the selected participants reward based on his/her history performances, i.e., the amount of high quality sensing data he/she contributed [13]. Yang et. al. defines that the amount of a participant's reward is the sum of rewards for other participants [45]. In general, using historical performance might be a good benchmark, certain pricing schemes [46], [47] need to be enforced to measure the data's true value in a mobile crowd sensing market. A lot of work can follow along this direction.

8 Conclusion and Future Work

In this paper, we proposed a novel incentive mechanism for quality-aware mobile crowd sensing. First, we introduced a mathematical model to characterize the quality of sensing data to be contributed by participants. Based on this, we presented a novel utility function as well as an optimization problem for the platform to maximize the collection of amount of high quality sensing data, subjected to limited budget. Then, we proposed an effective, quality-aware incentive mechanism to solve the problem, which showed to be truthful, individually rational, budget-wise feasible and computationally efficient. We compared our proposed scheme with existing methods via extensive simulations based on a real dataset. Results well justify that our approach achieves higher task accomplishment ratio by recruiting reputable participants while providing them satisfactory amount of reward, both basic and bonus part. For example, for the performance of task accomplishment, the proposed Online-QIM gains 21.7 percent more than that of OMG when budget is 100 units, and the propose mechanism also selects 55 percent more participants. And compared with OMG, the gap between the proposed Online-QIM and optimal method is reduce by 33.3 percent under budget $B = 1000$.

As for the future, we plan to design new incentive mechanisms by using deep reinforcement learning and consider perform real-world deployment and experiments on quantifying the people's reputation and reward.

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Hui Gao received the PhD degree from the State Key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications, China, in 2017. He is now with the School of Software, at the same university. His research interests include participatory sensing and the Internet-of-Things (IoT).

Chi Harold Liu (SM'15) received the BEng degree from Tsinghua University, China, in 2006, and the PhD degree from Imperial College, United Kingdom, in 2010. He is currently a full professor and vice dean with the School of Computer Science and Technology, Beijing Institute of Technology, China. He is also the director of the IBM Mainframe Excellence Center (Beijing), director of the IBM Big Data Technology Center, and director of the National Laboratory of Data Intelligence for China Light Industry. Before moving to academia, he joined IBM Research-China as a staff researcher and project manager, after working as a postdoctoral researcher at Deutsche Telekom Laboratories, Germany, and a visiting scholar at the IBM T. J. Watson Research Center. His current research interests include the Internet-of-Things (IoT), Big Data analytics, mobile computing, and deep learning. He received the Distinguished Young Scholar Award in 2013, the IBM First Plateau Invention Achievement Award in 2012, and the IBM First Patent Application Award in 2011. He was interviewed by EEWeb.com as the featured engineer in 2011. He has published more than 80 prestigious conference and journal papers and owned more than 14 EU/U.S./U.K./China patents. He serves as the area editor for the *KSII Transaction on Internet and Information Systems* and the book editor for six books published by Taylor & Francis Group and China Machinery Press. He also has served as the general chair of the IEEE SECON'13 Workshop on IoT Networking and Control, IEEE WCNC'12 Workshop on IoT Enabling Technologies, and ACM UbiComp'11 Workshop on Networking and Object Memories for IoT. He served as the consultant to the Asian Development Bank, Bain & Company, and KPMG, and the peer reviewer for the Qatar National Research Foundation, and National Science Foundation, China. He is a senior member of the IEEE.

Jian Tang received the PhD degree in computer science from Arizona State University, in 2006. He is a professor with the Department of Electrical Engineering and Computer Science, Syracuse University. His research interests lie in the areas of wireless networking, machine learning, big data, and cloud computing. He has published more than 120 papers in premier journals and conferences. He received an NSF CAREER award in 2009, the 2016 Best Vehicular Electronics Paper Award from the IEEE Vehicular Technology Society, and Best Paper Awards from the 2014 IEEE International Conference on Communications (ICC) and the 2015 IEEE Global Communications Conference (Globecom), respectively. He has served as an editor for a few IEEE journals, including the *IEEE Transactions on Big Data*, the *IEEE Transactions on Mobile Computing*, the *IEEE Transactions on Network Science and Engineering*, the *IEEE Transactions on Wireless Communications*, the *IEEE Internet of Things Journal*, and the *IEEE Transactions on Vehicular Technology*. In addition, he served as a TPC co-chair for the 2018 International Conference on Mobile and Ubiquitous Systems: Computing, Networking, and Services (Mobiquituous), the 2015 IEEE International Conference on Internet of Things (iThings), and the 2016 International Conference on Computing, Networking and Communications (ICNC); as the TPC vice chair for the 2019 IEEE International Conference on Computer Communications (INFOCOM); and as an area TPC chair for INFOCOM 2017-2018. He is currently the vice chair of the Communications Switching and Routing Committee of the IEEE Communications Society. He is a senior member of the IEEE.

Dejun Yang received the BS degree in computer science from Peking University, Beijing, China, in 2007, and the PhD degree in computer science from Arizona State University, in 2013. He is currently the Ben L. Fryrear assistant professor of computer science with the Colorado School of Mines. His research interests include economic and optimization approaches to networks, crowdsourcing, smart grid, and security and privacy. He also served as a TPC member for many conferences, including IEEE INFOCOM, ICC, and GLOBECOM. He received Best Paper Awards at IEEE GLOBECOM in 2015, IEEE MASS in 2011, ICC in 2011 and 2012, and the Best Paper Award Runner-up at IEEE ICNP in 2010.

Pan Hui received the bachelor's and Mphil degrees from the University of Hong Kong, and the PhD degree from the Computer Laboratory, University of Cambridge. He is the Nokia chair professor of computer science at the University of Helsinki, Finland. He is an ACM distinguished scientist, and also a distinguished scientist at Deutsche Telekom Laboratories (T-Labs), Berlin. During his PhD, he was also affiliated with Intel Research Cambridge. His research interests include delay tolerant networking, mobile networking and systems, planet-scale mobility measurement, social networks, and the application of complex network science in communication system design. He is a fellow of the IEEE.

Wendong Wang received both of the bachelor's and master's degrees from the Beijing University of Posts and Telecommunications, China, in 1985 and 1991, respectively. He is presently a full professor at the same university. He is currently serving on the Assessment Panel of the "National Natural Science Foundation" program and the "National High Technology Research and Development Program of China". He has published more than 200 papers in various journals and conference proceedings, and owned 14 US/China patents. His current research interests are the next generation network architecture, Internet-of-Things, participatory sensing, wireless ad-hoc, sensor and mesh networks, and mobile internet. He is a member of the ACM and the IEEE.