A QoS-Aware Online Incentive Mechanism for Mobile Crowd Sensing

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Abstract. Mobile crowd sensing has emerged as a compelling paradigm to provide sensing data for web information system. A number of incentive mechanisms have been proposed to stimulate smartphone users participation. The vast majority of work fails to take QoS into consideration. In general, QoS is of paramount importance as a standard criterion for mobile crowd sensing applications. In this paper, we propose a QoS-aware online incentive mechanism for maximizing the social welfare. In consideration of the dynamics, we design an approximation algorithm with $\frac{1}{2}$-competitive ratio to solve the online allocation problem. We conduct rigorous theoretical analysis and extensive experimental simulations, demonstrating that the proposed mechanism achieves truthfulness, individual rationality, high computational efficiency and low overpayment ratio.

Keywords: Mobile crowd sensing · QoS-aware · Dynamic smartphones

1 Introduction

With the rapid development of mobile computing, a growing number of web information systems or applications sets out to provide various real-time information services for general public [1,2]. The corresponding applications and web systems such as citizen emergency monitoring [3] have been investigated. Embedded with various sensors like microphone, GPS (*i.e.,* Global Position System), accelerometer, a smartphone can easily provide requisite sensing data for the requester. Thus, mobile crowd sensing has gained widespread popularity as a compelling paradigm to collect sensing data for web information systems [4].

Existing mechanisms face a common disadvantage. Various smartphone users have different QoS for given sensing tasks in most cases. Unfortunately, the fact is neglected in general. Traditionally, QoS is considered as a standard criterion of acquired web service per unit time [5]. Within the mobile crowd sensing application, QoS refers to the expected service quality of each smartphone user, as a significant criterion while the platform selects the winning smartphone users. Furthermore, smartphone users with higher QoS usually yield more value, leading to the increase of social welfare. Existing mechanisms [6] neglect the criterion of QoS. The similar work [6] to us is to assume the fixed value of each task.

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However, smartphone users usually have diverse QoS. Furthermore, budget constraint is considered for our condition.

This paper explicitly takes QoS of smartphone users into consideration in the design of incentive mechanisms. We propose a QoS-aware incentive mechanism to maximize the social welfare. In consideration of the online case, we design a near-optimal algorithm without future information about smartphone user's active time and the arrival of sensing task. Furthermore, We prove that our approximation algorithm achieves $\frac{1}{2}$-competitive ratio compared to the offline optimal solution. Rigorous theoretical analysis and extensive simulations are performed, and the result demonstrates that the proposed mechanism achieves truthfulness, individual rationality, high computational efficiency and low overpayment ratio.

2 System Model and Problem Definition

The mobile crowd sensing system consists of the platform, smartphone users and sensing tasks. Smartphone users arrive dynamically and sensing tasks are released at random. Let $\Gamma = \{\tau_1, \tau_2, ..., \tau_m\}$ denote the sequence of arrival of sensing tasks. M_i means the budget of the task τ_i arriving one after another in each slot t_i. Furthermore, one sensing task can be assigned to multiple smartphones to improve quality of sensing data returned by winning smartphones.

Let $w_j^{(i)}$ represent the j^{th} smartphone user arriving in slot t_i. The available smartphones are updated once new slot starts. Furthermore, let $N = \{1, 2, \ldots, n\}$ represent the snapshot of the pool smartphones at any slot t_i. Furthermore, we estimate his QoS for each task τ_i denoted as $q_j^{(i)}$ with the golden standard task sets [7] once a new smartphone j arrives.

Once a smartphone user arrives in the system, he has to submit the bid consisting of three parts $B_j = (\alpha_j, d_j, b_j)$, where α_j and d_j is the arrival and the departure time respectively with $0 < \alpha_j \leq d_j < m, 0 < b_j < \infty$ *(m is the largest slot within a single round)*. Consider the smartphone user is strategic, the real cost of each smartphone is remarked as c_j potentially unequal to the claimed cost b_i. We will make a detailed analysis in Sect. 4.

Suppose the platform tends to maximize the social welfare so that to meet both requester and smartphone user's demand for sustainable management. Every time a new sensing task τ_i comes, the platform determines to select what group from available smartphones who are active in the system without violating the budget constraint.

In generally, a compelling auction mechanism meets the condition of three properties: *truthfulness*, *individual rationality* and *computational efficiency*. Specifically, the smartphone utility is defined as $u(B_j) = p(B_j) - c(B_j) \cdot y(B_j)$, where the indicator variable $y(B_j)$ denotes if B_j wins, and $p(B_j)$ is the received payment. Meanwhile, the utility of sensing task τ_i allocated to bid B_j is $v^{(i)}(B_j) = q_j^{(i)} * \gamma - c(B_j)$, where γ denotes the value of unit QoS and $q_j^{(i)} \in (0, 1)$.

Our QoS-aware incentive mechanism consists of *winning user selection algorithm* and *payment decision scheme*. The set S_i of available smartphone users is updated dynamically once a new task arrives. Thus, we demonstrate the offline problem as IP (Integer Programming) problem in Definition 1.

Definition 1 (winning user selection Problem (WUSP)). *The winning user selection problem is shown as follows:*

$$\max \sum_{i=1}^{m} \sum_{j=1}^{n} y^{(i)}(B_j) \cdot v^{(i)}(B_j) \tag{1}$$

$$s.t. (\sum_{j=1}^{n} y^{(i)}(B_j) \cdot c(B_j)) \leq M_i, \; for \, \forall i \in \Gamma \tag{2}$$

$$\sum_{i=1}^{m} y^{(i)}(B_j) \leq 1, \; for \, \forall j \in S_i \tag{3}$$

$$\alpha_j \leq i \leq d_j, \; if \, y^{(i)}(B_j) = 1 \tag{4}$$

$$y^{(i)}(B_j) \in \{0, 1\}, \; \forall (i, j) \tag{5}$$

Remarks: The first constraint (2) demonstrates for each sensing task, the sum of assigned smartphone users' real cost should not violate the reserve budget. The second constraint (3) means that each smartphone user is assigned at most one task within his active time. The third constraint (4) restricts the winning slot within his active time for each smartphone user.

Definition 2 (Payment Decision Problem (PDP)). *The payment decision problem is to compute the payment for each winning smartphone user.*

In the following section, the design and key algorithms about the online case will be presented further.

3 Design of QoS-Aware Online Mechanism

In this section, we consider the online case, which is consistent with the realistic condition. We solve the proposed two problems in Sect. 2 consisting of the approximation algorithm for winning user selection and payment decision scheme with truthfulness guarantee.

3.1 Online Approximation Algorithm for WUSP

The online greedy algorithm (*OGA*) is proposed to solve the WUSP. The main idea is to allocate the smartphone user with the highest metric (called cost performance) from current set of available smartphone users to each incoming sensing task until the reserve budget is exhausted. We first give the definition of *cost performance* of the smartphone user as follows.

Algorithm 1. Online Greedy Algorithm(OGA)

Input Set B of bids, set $\boldsymbol{M} = (M_1, \ldots, M_m)$ of reserve budget.
Output Allocation scheme A consisting of scheme of single task A_i.

$t \leftarrow 1$, $S_t \leftarrow \emptyset$, $A_i \leftarrow \mathbf{0}$;
while $t \leq m$ **do**
  Update current available smartphone users S_t and the size is recorded as $|S_t|$ add new smartphone users arriving at slot t and delete ones who have left at slot t;
  Invoking function *UQA* for each new smartphone user j *(UQA is omitted)*;
  Sort all available smartphone users with the cost performance metric $\boldsymbol{r_j}$ in the decreasing order.
  for round r from 1 to $|S_t|$ **do**
    if $M_t \neq 0$ **then**
      Choose the first smartphone user j in S_t, $A_i(j) \leftarrow 1$;
      $S_t \leftarrow S_t - j$, $M_j \leftarrow M_j - c_j$;
      if $M_t < 0$ **then**
        $A_i(j) \leftarrow 0$, $M_j \leftarrow M_j + c_j$;
      end if
    end if
  end for
  $t \leftarrow t + 1$.
end while
return $A = (A_1; A_2; \ldots; A_m)$;

Definition 3 (Cost Performance). *The cost performance is the metric of the greedy algorithm to select the winning smartphone users, meaning QoS* $q_j^{(i)}$ *divided by the claimed cost* c_j *for any smartphone user* j*.*

$$r_j = \frac{q_j^{(i)}}{c_j} \tag{6}$$

Remarks: The QoS of each smartphone user is estimated based on golden standard sets [7]. In consideration of space limit, we omit the part.

Next, we demonstrate the process of the online greedy algorithm in each slot. The online greedy algorithm is executed at the start of each slot. Once a new slot i comes, currently available smartphone users S_i are updated, meaning that new smartphone users join the system and old ones leave according to the active time of their separate bids. Next, we compute the cost performance metric r_j for any new smartphone user j. Then, we select the smartphone user with the highest metric. Meanwhile, the corresponding budget M_j subtracts his cost until it becomes zero. The pseudo-code is shown Algorithm 1.

3.2 Payment Decision Scheme

Payment decision scheme is proposed to solve the PDP. Because online greedy algorithm is the suboptimal solution, the traditional VCG mechanism [8] cannot be applied to our payment decision scheme. Thus, we design a non-VCG mechanism [6] to induce smartphone users to disclose their cost truthfully. Note that we assume that sufficient smartphone users are available when new sensing task comes so as to avoid monopoly.

The main idea is to find his *critical user* for each winning smartphone user. Furthermore, the claimed cost of the *critical user*, called *critical payment*, is considered as the reward. Suppose that the QoS of each smartphone user is constant once estimated. For any winning smartphone user j, the critical user $c(j)$ is the first smartphone user who makes current winning user j fail, who is determined as follows: if current winning user j claims a higher cost than that of critical user $c(j)$ user j loses, while user j still wins on the contrary.

Next, we demonstrate how to find the critical user $c(j)$ for each winning user j. For the bid $B_j = (\alpha_j, d_j, b_j)$, suppose that the smartphone user j wins in slot t_j where $\alpha_j \leq t_j \leq d_j$. We run the online greedy algorithm while deleting current winning smartphone user j. Especially, we record the winning smartphone user with the highest claimed cost as the critical user $c(j)$ from the winning slot t_j to the departure slot d_j. The details of the payment scheme are demonstrated as Algorithm 2.

4 Theoretical Analysis

In this section, we list the key properties of our mechanism. However, the detailed proofs are omitted due to the page limit.

According to [8], the mechanism is truthful if and only if it meets the two following conditions of *monotonicity* and *critical value*.

Definition 4 (Monotonicity). *For any smartphone user j with bid $B_j = (\alpha_j, d_j, b_j)$, if j submits the bid $\tilde{B}_j = (\tilde{\alpha}_j, \tilde{d}_j, \tilde{b}_j)$ where $\tilde{\alpha}_j \leq \alpha_j$, $\tilde{d}_j \geq d_j$ and $\tilde{b}_j \leq b_j$, he also wins.*

Definition 5 (Critical Value). *For any smartphone user j with bid $B_j = (\alpha_j, d_j, b_j)$, there exists a critical value $p_j^{(c)}$. If j submits a lower bid $B_j = (\alpha_j, d_j, p_j^{(c)} - \sigma), \sigma > 0$ he still wins. On the contrary, he declares a higher bid $B_j = (\alpha_j, d_j, p_j^{(c)} + \sigma), \sigma > 0$, j loses.*

Theorem 1. *The proposed online auction mechanism is truthful.*

Theorem 2. *The proposed online auction mechanism meets the property of individual rationality.*

Theorem 3. *The key algorithms including* OGA *and* CPDS *of the proposed online auction mechanism have polynomial computational complexity.*

Theorem 4. *The online greedy algorithm* OGA *has $\frac{1}{2}$-competitive ratio compared to the offline optimal solution.*

Algorithm 2. Critical Payment Decision Scheme(CPDS)

Input Set B of bids, the winning smartphone user j, the winning slot t_j.
Output payment p_j of the smartphone user j.

$t \leftarrow 1$, $S_t \leftarrow \emptyset$, $p_j \leftarrow b_j$, $B \leftarrow B - B_j$;
while $t \leq d_j$ **do**
  Update current available smartphone users S_t and the size is recorded as $|S_t|$ add new smartphone users arriving at slot t and delete ones who have left at slot t;
  Invoking function UQA for each new smartphone user j *(UQA is omitted)*;
  Sort all available smartphone users with the cost performance metric $\boldsymbol{r_j}$ in the decreasing order.
  for round r from 1 to $|S_t|$ **do**
    if $M_t \neq 0$ **then**
      Choose the first smartphone user j in S_t, $A_i(j) \leftarrow 1$;
      $S_t \leftarrow S_t - j$, $M_j \leftarrow M_j - c_j$;
      if $M_t < 0$ **then**
        $A_i(j) \leftarrow 0$, $M_j \leftarrow M_j + c_j$;
      end if
    end if
  end for
  if $t \geq t_j$ **then**
    Obtain the maximum cost $c_{max}(t)$ from current winning set A_t;
    if $c_{max}(t) > p_j$ **then**
      $p_j \leftarrow c_{max}(t)$;
    end if
  end if
  $t \leftarrow t + 1$;
end while
return p_j;

5 Performance Evaluation

We conduct extensive simulations to evaluate the performance of our proposed online auction mechanism. Under the following two metrics, *i.e.,* overpayment ratio and social welfare, we evaluate the claimed cost of smartphone users under three distributions, *i.e.,* normal distribution ($NORM$), exponential distribution (EXP) and uniform distribution (UNM). Especially, for normal distribution with mean μ, we set the standard deviation σ so that 99.73% samples fall within $[\mu - \sigma, \mu + \sigma]$, *i.e.,*$\sigma = \frac{50-\mu}{3}$. The overpayment is the difference between total payments and total real costs of all winning smartphone users. Thus, the overpayment ratio is the overpayment divided by total costs. We omit the definition of the limit of space.

Furthermore, we simulate dynamic smartphone users under Poisson distribution. Other default settings are shown as Table 1. Finally, we show the experimental result as follows.

Table 1. Summary of default settings

Parameter name	Default value
Arrival rate λ of smartphones	400
Average of real costs $\bar{c}$	25
Range of real costs $\bar{c}$	[0,50]
Number of slots m	100
Average length of active time	10

Figure 1 plots the overpayment ratio when the arrival rate λ of smartphone users increases from 100 to 700 under three distributions. We observe that the overpayment ratio keeps low and stable with the increase of the number of smartphone users, meaning that our system has strong stability. The overpayment under normal distribution is much lower than those of uniform distribution and exponential distribution. This is because, the critical payment of the smartphone user is closer to the mean μ. Recall that 99.73% samples fall around μ. Thus, it leads to low overpayment ratio.

In Fig. 2, we find that social welfare ω under three distributions increases when there are more smartphone users arriving in each slot. Obviously, with more smartphone users, the platform can find more users with high cost performance, inducing the increase of social welfare. Note that social welfare under the exponential distribution is much higher than those of other two distributions. The reason is that more smartphone users with lower cost are generated under exponential distribution. Consider there are sufficient smartphone users in the system. Thus, the platform can select more smartphone users with high cost performance.

We obtain the similar result to Fig. 1 from Fig. 3, plotting the overpayment ratio with more slots m. The result shows that even more sensing tasks lead

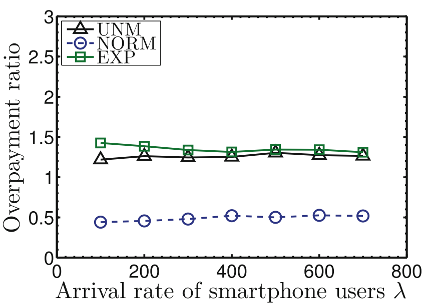

Fig. 1. Overpayment ratio vs. Arrival rate λ of smartphones.

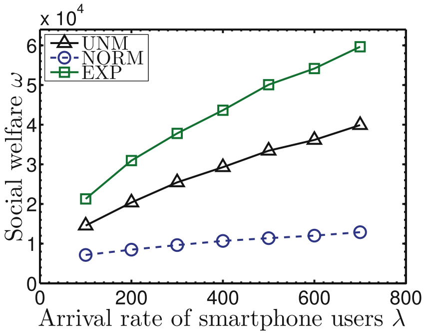

Fig. 2. Social welfare ω vs. Arrival rate λ of smartphones.

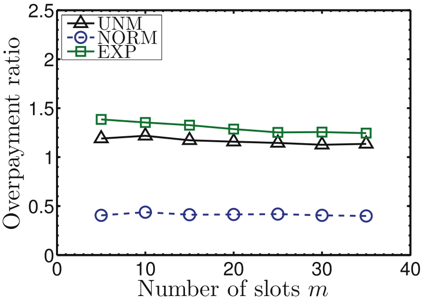

Fig. 3. Overpayment ratio vs. Number of slots m.

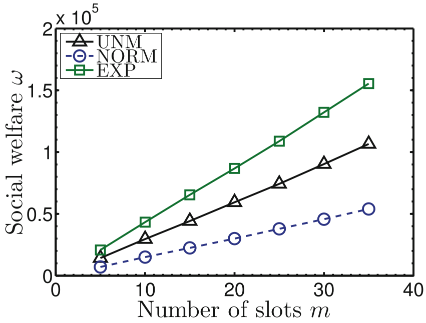

Fig. 4. Social welfare ω vs. Number of slots m.

to more assigned smartphone users, which would not increase the overpayment ratio. Thus, the system can achieve long-term run.

In Fig. 4, we observe that social welfare ω increases under three distributions when the number of slot m increases. Obviously, more sensing tasks are assigned, leading to the addition of the social welfare.

6 Conclusions

In this paper, we design a QoS-aware incentive mechanism towards dynamic smartphone users and sensing tasks with budget constraint. Two key algorithms consisting of winning user selection algorithm and payment decision scheme are proposed. In consideration of dynamics, we design a near-optimal online allocation algorithm to achieve $\frac{1}{2}$-competitive ratio. Meanwhile, a truthful payment decision scheme is proposed for suboptimal allocation solution. Extensive simulations are performed, and the results show that the proposed mechanism achieves the desired properties of truthfulness, individual rationality, high computational efficiency and low overpayment ratio.

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