A Participant Selection Method for Crowdsensing Under an Incentive Mechanism

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Abstract. With the rich set of embedded sensors installed in smartphones, a novel applications is emerged, i.e., Mobile Crowdsensing (MCS). Generally speaking, in a MCS application, each participant often gets equal reward. In some situations, this assumption is unfair for some valuable participants. With this observation, a novel framework is investigated in this paper with an incentive mechanism, instead of assuming that each participant should get equal reward. As a result, our method is validated by experiment enabled by real-life datasets.

Keywords: Mobile crowdsensing · Participant selection

1 Introduction

Nowadays, there is an increasing demand to retrieve the information of real-time air quality, noise level, speed of mobile network, etc. With this observation, Mobile Crowdsensing (MCS) is becoming a popular alternative technique to collect the time-sensitive and location-dependent information [5–7]. In a MCS application, a smart phone plays as a mobile sensor, which could display time-sensitive and location-sensitive information in a real-time way. In a MCS application, participant recruitment is a key issue. For achieving more and more information, participant should be attracted with a certain incentive mechanism. For example, in many MCS application, incentives are paid for attracting more and more volunteers to collect more and more information. On the other hand, a MCS application is often promoted with a certain budget. The total cost of a MCS system limited the scale of the participants. For example, in [9,10], some methods is presented, aiming at selecting a small number of participants to minimize the total cost in a MCS system. With these observations, we could find that it is a challenge to balance the budget and the scale of participants in a trade off way. Moreover, with certain budget, it is another challenge to set up an incentive mechanism. This incentive mechanism could lead the participants

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to cover all the area in an expected distributed way, which a MCS application system is interested. In view of this challenge, in this paper, a participant selection method is presented aims at trading off the relationship between the budget and the scale of participants in an expected distributed way. To the best of our knowledge, there is few works that consider these issues in a comprehensive way.

The rest of this paper is organized as follows. In Sect. 2, we present the system framework and define the problem. In Sect. 3, a two stage algorithm is designed to select participants. Section 4 experiment and evaluation are investigated. In Sect. 5, related works are discussed. Section 6 concludes the paper.

2 Problem Formulation and System Framework

2.1 System Model

Suppose that there is a continuous sensing task in our MCS system. In addition, there are a certain amount of participants which we denote $\mathbf{U}$ and their history trace information denoted by set $\mathbf{D}$ over a period of time. Our platform should divides this task into many sub-tasks, allocates each participant some sub-tasks and fairly give each participant rewards. After the completion of a sensing task, the smartphone returns the sensing data back to the platform which then manipulates the data and at last, forward the information to users. For a sub-task allocated to a participant, he may fail to complete. Therefore, we would allocate a sub-task to many participants to insure a low fail probability in a sensing area which we call it Probabilistic Coverage Constraint.

Before formally defining the problem of the sensing task allocation, we first introduce some notations defined as followed.

Definition 1 (Sensing Task). *In our MCS system, we divide our sensing task into* N *sensing area during* T *sensing circle, which we denote a sub-task in* $j-th$ *sensing area during* $k-th$ *sensing circle as* H_{jk}.

Definition 2 (Probabilistic Coverage Constraint (PCC)). *In our system, we would allocate a sub-task in a* H_{jk} *to some participants. For obtaining accurate information in it, we need control a maximum fail probability* C_{jk} *which all selected participants fail to complete this task. Therefore, in a* H_{jk}*, we need satisfy the constraint*

$$1 - \prod_{i=1}^{|\boldsymbol{S}|}(1 - P_{i,j,k}) \geq C_{jk} \tag{1}$$

where $P_{i,j,k}$ *is the probability the i-th participant fail to complete sensing task in* H_{jk}.

Definition 3 (Adjoint Set). *If a sensing area of a* H_{jk} *is adjacent to another one* $H_{\hat{j}\hat{k}}$*, we call they are adjoint denoted as* $\simeq$*. Hence, a set* $\boldsymbol{A}_j, \{H_{\hat{j}\hat{k}} | H_{jk} \simeq H_{\hat{j}\hat{k}}\}$*, is a adjoint set of* H_{jk}.

2.2 Participants Selection Problem Formulation

In our system, we need to select a number of participants denoted by set $\mathbf{S}$ to help us complete a continuous task. A participant's incentive is consisted of base fees and additional fees which is related to the sub-tasks they complete. Hence, the total incentives in MCS system are

$$F = \sum_{i=1}^{|\mathbf{S}|} f + \sum_{i=1}^{|\mathbf{S}|} \sum_{j=1}^{N} \sum_{k=1}^{T} v_{jk} \cdot w_{ijk} \tag{2}$$

where w_{ijk} denote whether the i-th participant upload the information in j-th sensing area during t-th sensing circle.

Our MCS system would minimize the total incentives F while satisfying the Probabilistic Coverage Constraint in each sensing area during all sensing circles. The problem is to find $\mathbf{S}$ as a subset of $\mathbf{U}$, with the objective to

$$\min_{\mathbf{S}} E(F), \ \ s.t. \ Cov_{jk}(|\mathbf{S}|) \leq C_{jk} \tag{3}$$

where $0 \leq j \leq N, 0 \leq k \leq T$ and $Cov_{jk}(|\mathbf{S}|)$ is a probability that the participants in $\mathbf{S}$ complete the sub-task in H_{jk}.

3 Two Stage Algorithm

Participants' selection problem under incentive mechanism is NP-Hard. Because when we set $v_i = 0$, the problem is reduced to the participants' selection problem which has been proved to be NP-hard. In the next section, we use a two-stage algorithm to solve it.

3.1 Two-Stage Approximation Algorithm

Brute-Force Stage. In this stage, we enumerate all $\mathcal{O}(kn_k)$ possible subsets of objects that have up to k objects. Although the combinatorial number is easy to be calculated, the enumeration of a set is not easy. The steps of our algorithm is specified as following. We use a boolean array B to represent the enumeration of all sets. If the i-th value in B is 1, it represents that the $i-$th element in $\mathbf{U}$ is in this set. (1) We first set the first k elements as 1 in B and meanwhile record it in List L where we store the final enumeration. (2) Then, we find the first 10 sequence in position p in B and transform it to 10. (3) After that, we shift each 1 to right position before position p. Meanwhile, we would store each transformation into L. We repeat these option (2) and (3) till the right k position in B is all 1.

Algorithm 1. Parallel Greedy Stage

```
Input: $L$ $Prodc_{jk}$
Output: List $P_S$
Initialize Array $Q$ with equation (13) and decreasing it.
$P_S = L$.
Divide $L$ to $L_1, L_2, ..., L_p$.
Do with each $L_p$ on parallel
for $u = 0$ to $L_p.length$ do
    for $i = 0$ to $Q.length$ do
        Ergodic each sensing area $H_{jk}$
        $cov_{jk} = Prodc_{jk} * (1 - Q[i].P_{i,j,k})$;
        if $cov_{jk} > 1$ then $flag = 1$;
        end if
        if $flag == 0$ then $P_S \leftarrow i$;
        end if
    end for
end for
```

Parallel Greedy Stage. For each subset recruited by the brute-force stage, we use the greedy algorithm to fill up the rest of the "knapsack". In this stage, we design a quality function to help us select the participants.

$$Q(i) = \sum_{j=1}^{N} \sum_{k=1}^{T} \frac{(1 - P_{i,j,k})}{(1 - C_{jk})} * F_i \tag{4}$$

where $\frac{1-P_{i,j,k}}{1-C_{jk}}$ stands for the ratio that a object occupies the knapsack. Therefore, $Q(i)$ stands for ratio of profit to size or profit density in our algorithm. To each subset calculated in stage 1, we can apply our greedy stage to fill up them on parallel. Therefore, we divide the List L into p sub-lists, $L_1, L_2, ..., L_p$ and respectively run on p physic machines or cores. In Algorithm 1, we specify the procedure of the greedy stage.

4 Evaluation

We evaluate the performance of our algorithms using real-life data traces and experiments. The dataset we used in evaluation is the GeoLife GPS Trajectory dataset, which was collected in (Microsoft Research Asia) Geolife project by 182 users in a period of over three years.

Table 1 specifies the performance comparison between TSA and baseline methods with different F and $E(V_{ij})$. It is easy to find that TSA always selects participants which are paid lower total incentives than other three methods. Although the number of participants selected by TSA is not always lowest in these four methods, the total incentives is lowest. When F is lower than $E(V_{ij})$, the number of participants TSA selects is not least int the four methods. When F is bigger than $E(V_{ij})$, TSA could select the least participant than other three

Table 1. The Performance Comparison between TSA and baseline methods with different F and $E(V_{ij})$

(a) $F = 0$, $E(V_{ij}) = 50$			(b) $F = 100$, $E(V_{ij}) = 50$		
	Number	Cost		Number	Cost
TSA	125	308.26	TSA	122	12208.70
MaxMin	182	312.29	MaxMin	182	18512.23
MaxCov	120	309.73	MaxCov	120	12309.73
MaxCom	131	310.72	MaxCom	131	136504.57

methods. It is good property that TSA could also solve the original participants selection problem with assumption that each participant should be paid equal as long as we set $E(V_{ij}) = 0$.

In summary, it can be concluded that TSA is better than other three baseline methods. In despite of the slightly long running time, the overall performance of the TSA is pretty good.

5 Related Work

Participant Selection Problem in MCS. In [8], Reddy *et al.* first study the research challenge of participant recruitment in participatory sensing, they propose a coverage-based recruitment strategy to select a predefined number of participants so as to maximize the spatial coverage. More recently, Zhang D propose a novel participants selection framework for mobile crowdsensing, which operate on top of energy-efficient Piggyback Crowdsensing and minimizes incentive payments by selecting a small number of participants while still satisfying PCC.

Incentive Mechanism in MCS. Incentive mechanism is an important research direction [1,2]. Existing crowdsensing applications and systems lack good incentive mechanisms that can attract more user participation. Game theory has widely been used in incentive mechanism design in MCS systems, which is try to capture and tackle usrs' strategic behaviors. In addition, there are also some studies on designing recruitment/incentive mechanisms for participatory sensing [3,4].

6 Conclusion

In this paper, we present a novel participant selection framework supporting Mobile Crowdsensing system development. In a MCS, each participant need complete some tasks that the system allocate and accordingly get rewards. Instead of assuming each participant get the same rewards in an MCS, we introduce a incentive mechanisms to evaluate each participant's incentives and then select suitable participants to minimize the total cost in an MCS. Our method is promoted by PG game theory. Experiments validated our method, and in the future, some real Mobile Crowdsensing system will be used to validate our method in a pervasive way.

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