A Reverse Auction Incentive Mechanism Based on the Participant's Behavior in Crowdsensing

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Abstract. Crowdsensing has been integrated into many aspects of human life. Compared with the general mode of perception which need to arrange a large number of sensors in advance, crowdsensing uses the idea of crowdsourcing to distribute tasks to participants carrying mobile sensing devices with them, which can save the cost of deploying sensing nodes. Therefore, how to make people actively participate in perception has become a hot issue. The existing incentives mainly include bonus incentives, game entertainment incentives, and social relationship incentives. This paper proposes a reverse auction incentive mechanism based on the participant's behavior. Specifically, we analyze the user's behavior and build a model of participant competency assessment firstly; then, according to the above analysis, each user is scored and the reward is distributed using the improved reverse auction algorithm. The experimental results show the effect of the proposed method.

Keywords: Crowdsensing · Incentive mechanism · The participant's behavior · Privacy protection

1 Introduction

With the development of wireless communication and smart mobile devices, life is becoming more and more intelligent. From smart homes to smart cities, Internet of Things (IoT) technology has been integrated into all aspects of human life. Crowdsensing is also a new perception mode of IoT. Crowdsensing is a way which uses people carrying mobile sensing devices with them as the basic unit of perception. Compared with the general mode of perception, crowdsensing need arrange a large number of sensors in advance. The crowdsensing system assigns the task to the participants. Participants upload their own sensing data with the mobile devices and act as sensors. The most important thing in crowdsensing is how to improve the enthusiasm of user participation. In the crowdsensing system, there are many different incentives. It can be divided into money-based

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incentives and non-money-based incentives. Krontiris, Lee and Rula et al. have proposed some incentives for bonus incentives [1–3] and the money-based incentive mainly to encourage participants to participate through the payment of rewards. The monetary incentive is the auction mechanism which is to complete the quotation of the perceived data by the participants and select the subset of participants with lower payment cost. And the remuneration payment incentives is the main incentive currently [4]. Non-money-based incentives mainly include entertainment game incentives, social relationship incentives and virtual point incentives. Entertainment game motivation refers to the use of the game's entertainment and attraction to motivate users to complete the perception task by introducing the game strategy into the group perception system such as Kawajiri et al. proposed Steered crowdsensing: incentive design towards quality-oriented place-centric crowdsensing [5] and Han et al. proposed an enhancing motivation in a mobile participatory sensing project through gaming [6]. Social relationship incentives refer to a certain social network relationship built by the existing or server platform in which the participant is located [7,8]. The participants are motivated to maintain a sense of belonging in the social relationship. The virtual point incentive means that the participant will In the perceived task, virtual points are rewarded [9,10]. The real money converted from virtual points, some kind of physical object or the virtual reward sent by it will encourage users to participate in the perception task. However, many scholars have ignored the issue of user behaviour and user privacy. In this paper, we propose a reverse auction incentive mechanism based on the participant's behavior which consider the user privacy.

The rest of the paper is organized as follows. Section 2 construct the model of participant competency assessment. Section 3 presents a reverse auction incentive mechanism based on participant's behavior. Section 4 describes the experiment and results. Finally, we conclude our work in Sect. 5.

2 The Model of the Competency Assessment of the Participant

2.1 Evaluate the Participant's Positional Participation Ability

Dividing the Area. When the crowdsensing system plans to perceive the data, the first thing that needs to be done is the determination of the geographic location. Most researchers use GPS positioning to determine the geographic location of a participant. However, the GPS positioning is accurate, which poses a threat to the participant's location privacy, thus affecting the participants' enthusiasm for participation. In this paper, we considers the characteristics of the above situation to divide the geographical location into regions. When the region is divided, the adjustment parameters can be modified to arbitrarily enlarge and reduce the region, which is more flexible than the traditional division method.

Calculate the number of longitude partitions ($longitude_{zone}$) and latitude partitions ($latitude_{zone}$) based on the measuring range. The method is defined as follows:

$$longitude_{zone} = \frac{longitude_{max} - longitude_{min}}{\alpha}, \tag{1}$$

$$latitude_{zone} = \frac{latitude_{max} - latitude_{min}}{\beta}. \tag{2}$$

Where, the $longitude_{min}, longitude_{max}, latitude_{min}, latitude_{max}$ is the maximum and minimum values of the measurement range. α, β is the parameter of partition.

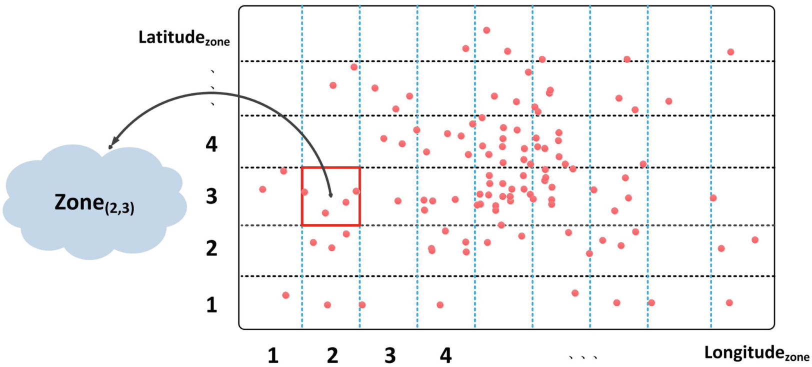


Fig. 1. Divided area.

As shown in Fig. 1, the partitioning formula can be obtained from the partitioning formula $latitude_{zone} \times longitude_{zone}$. Record the partition as $Zone_{i,j}, i \in [0, latitude_{zone}], j \in [0, longitude_{zone}]$, and calculate the area where the participant is located according to the coordinates of the participants. Methods as below:

$$Zone_j = \frac{lo - longitude_{min}}{\alpha}, \tag{3}$$

$$Zone_i = \frac{la - latitude_{min}}{\beta}. \tag{4}$$

Where lo is the longitude of the location where the participant uploaded the data and la is the longitude of the location where the participant uploaded the data. α, β is the parameter of partition.

Hot Spot Area. The crowdsensing task requires participants to collect information about each location. The more participants and the more data collected by the participants, the more data the server gets, and the better the data needed for the location. In this paper, we define the participant's location activity ability according to the distance between the participant's data area and the hot spot area. The farther away the participant is from the hotspot area, the more meaningful it is for data users, and the stronger the participant's positional activity ability. Most of the participants will collect the data which from hotspots. So, the closer the participant is to the hot spot area, the more meaningless it is for data users, and the weaker the participant's positional activity ability. It will encourage more participants to collect data in remote locations. It is also possible to collect as much data as possible from remote areas to more realistically reflect the situation at that location. As shown in Fig. 2, the partition type can be roughly divided into four types according to the daily activities of the participants:

Type 1: uploading intensive information.
Type 2: uploading more information.
Type 3: uploading less information.
Type 4: uploading no information.

The hot spot area is area which has the most number of participants and the most number of data uploads. The type 1 will appear in sub-area and the hot spot area. Before defining a hot spot area, the first thing that need to define is the participation status of participants in each area, which is defined as follows:

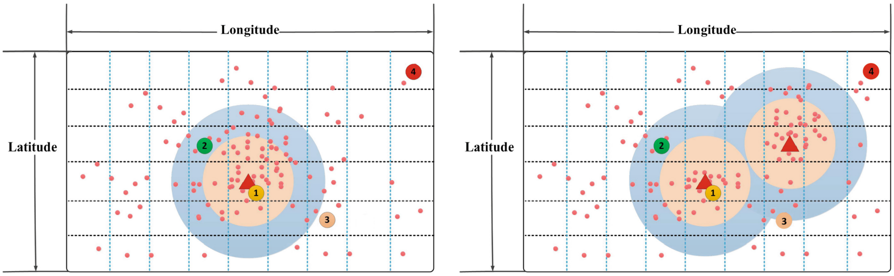
$$Zone(i,j) = \frac{N\_Zone_{(i,j)}}{N\_all} + \frac{NU\_Zone_{(i,j)}}{NU\_all}, \tag{5}$$

Where N_all is the number of data uploaded by all users of a task. $N\_Zone_{(i,j)}$ is the number of data in the area numbered (i,j) for all users in the area. NU_all is the number of users participating in a task. $NU\_Zone_{(i,j)}$ is the number of users participating in the task in $Zone_{i,j}$.

Calculate the $Zone(i,j)$ value for each region and define the maximum value in $Zone_{i,j}$ as $max(i,j)$. Usually there is only one hot spot area which named as $ZoneHot_{i,j}$, we define the maximum value in $Zone_{i,j}$, that is, $max(i,j)$ as the hot spot area. However, it does not rule out that there is a case where the maximum value and the next largest value of $Zone_{i,j}$ are extremely small. In this case, it is obviously inappropriate to define a hot spot area, so both the maximum value and the sub-value area are defined as hotspot areas. By analogy, multiple hot spot areas ($ZoneHot_{i,j}$) can be set, but depending on the size of the area, the hot spot area is limited in number. The specific definition is as follows:

$$Zone_{hot}(i,j) \in \{Zone(i,j) | max(i,j) - Zone(i,j) \leq a\}, \tag{6}$$

Where a is the difference between $max(i,j)$ and $Zone(i,j)$, and all regions in which the difference is within this range are defined as hot spot regions, $Zone_{hot}(i,j)$ is the $Zone(i,j)$ value of the hot spot area ($ZoneHot_{i,j}$).



(a) One Hot Spot. (b) Multiple Hot Spots.

Fig. 2. Hot spot area. (Color figure online)

Assessment Method. According to the regional hot spot [11], the participant's positional activity ability can be defined by calculating the distance between the participant and the hot spot area. As shown in Fig. 2(a), the hot spot area (the area marked by the triangle in the figure) is the center of the circle. In this study, the farther away from the center of the circle (hot spot), the more active the participants are, and the more information is collected. value. When there is only one hot spot area, since the blue circle is farther away from the hot spot area than the yellow circle, it is considered that the positional activity ability of the participants in the blue circle is stronger than the positional activity of the participants in the orange circle. As shown in Fig. 2(b), when there are multiple hot spot areas, the average distance between the area where the point is located and the hot spot area is taken. Commonly used methods for calculating distance include Euclidean distance, Manhattan distance, standardized Euclidean distance, cosine distance, and Chebyshev distance. In this study, the area measured by the task is divided into equal-sized areas. This structure is closer to the definition of Chebyshev distance [12], so the participant's position activity ability is defined as follows:

$$PZone = \frac{\sum_{m=1}^{n_{hot}} |Zone_{i,j} ZoneHot_{i,j}|}{n_{hot}} \times \tau, \tag{7}$$

$$|Zone_{i,j} ZoneHot_{i,j}| = max\{|i - i_{hot}|, |j - j_{hot}|\}, \tag{8}$$

where τ is the capability parameter and n_{hot} is the number of hot spots.

2.2 Evaluate the Participant's Time Participation Ability

In the crowdsensing task, the time the participants spend on the task is also an important indicator to measure the ability of the participants. The longer the participation time, the stronger the participant's time participation ability. Every task posted by the server has an expiration date. As shown in the Fig. 3, this article divides 24 time zones into 24 time zones. The time the participant participates in the task and the amount of information the user uploads after

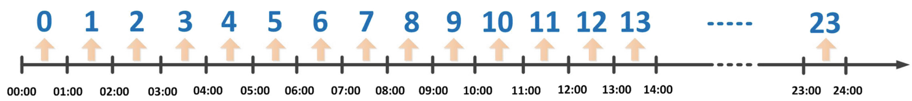


Fig. 3. Assess the participants time participation ability.

accepting the task will affect the evaluation of the user. Therefore, the time participation ability is defined as:

$$TTPR = \sum_{i=1}^{e} Task_i, \tag{9}$$

$$Task = \frac{Actask}{Atask} \times \chi, \tag{10}$$

where $AcTask$ represents the actual participation time of each user. $ATask$ indicates the time of a task. Task is the proportion of time each user participates in the task, and χ is the adjustment parameter. e is the number of times collected by the user.

2.3 The Competency Assessment of the Participant

According to the above description, the participant's ability is mainly divided into the participant's time participation ability and the participant' s positional activity ability, which are defined as follows:

$$Capacity = \theta \times \frac{\sum_{i=1}^{n} PZone_i}{n} + \mu \times TTPR_i, \tag{11}$$

where $TTPR_i$ is the participant's time participation ability, $PZone_i$ is the participant's position participation ability, n is the number of data collected by the participant in a certain task, and θ, μ are adjustment parameters which $\theta + \mu = 1$.

3 A Reverse Auction Incentive Mechanism Based on the Participant's Behavior

3.1 The Participant's Comprehensive Ability Value

In the reverse auction incentive mechanism based on participant behavior, the participants' comprehensive capabilities are defined as the average comprehensive ability value of all participants is taken as the threshold value of the bonus, which is defined as follow,

$$Threshold = \frac{\sum_{i=1}^{N} Capacity_i}{N \times \varphi}, \tag{12}$$

where Threshold is the critical value, N is the total number of participants, and $Capacity_i$ is the comprehensive ability of each participant. φ is the adjustment parameter.

3.2 An Incentive Mechanism Based on the Participant's Capacity

The reward given by the crowdsensing task is ω. When the participant's capacity is lower than the threshold value, the participant does not receive the bonus. When the participant's capacity is above the threshold, the participant's bonus will be paid. The higher the participant's total ability value, the more the reward W_i the task pays to the participant. The relationship is as shown in the following formula.

$$W_i = \frac{Capacity_i}{\sum_{j=1}^{k} Capacity_i} \times \omega, \tag{13}$$

where W_i is the bonus paid to the participant i for the task. k is the number of participants whose comprehensive ability is higher than the threshold. $Capacity_i$ is the comprehensive ability of each participant. ω is the total compensation of the participants given by the task.

4 Experiment and Result Analysis

4.1 Set Up

In this paper, we use the Gowalla data set which is a location-based social networking website where users share their locations by checking-in and consists of 196,591 nodes to analyze the experiment [13]. It have collected a total of 6,442,890 check-ins of these users over the period of Feb. 2009–Oct. 2010. In experiment, we selected two groups of data which user number is $0-49$. The one is the data in 8. Oct. 2010–10. Oct. 2010 interval named $Task_1$, the other is the data in 1. Oct. 2010–31. Oct. 2010 interval named $Task_2$. The experimental parameters are set as Table. 1. Then, we divide latitude and longitude partitions and mark the user point in the partition which are shown in the Figs. 4 and 5. Figure 4 is the distribution of users in $Task_1$ and Fig. 5 is the distribution of users in $Task_2$.

Table 1. The simulation parameters

No	Parameter	Value	No	Parameter	Value
1	α	0.5	7	m	1
2	β	2	8	n	50
3	a	5	9	θ	0.5
4	τ	0.1	10	μ	0.5
5	χ	100	11	φ	1
6	n_{hot}	2,4	12	ω	1000

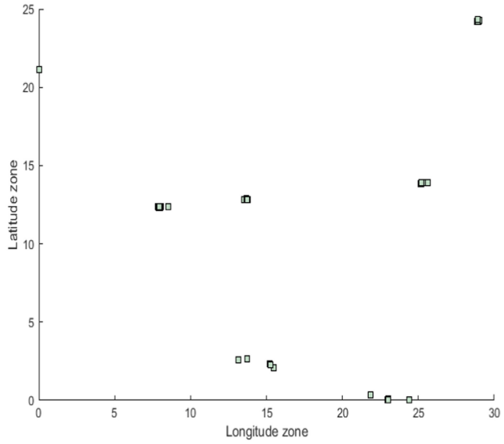


Fig. 4. Latitude and longitude partition of Task1.

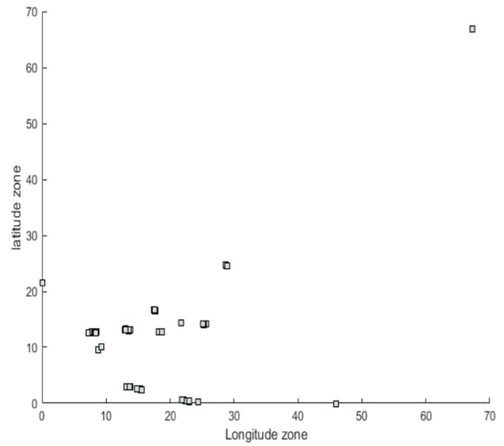


Fig. 5. Latitude and longitude partition of Task2.

4.2 Result Analysis

By the data set in the experiment, we can not accurately evaluate the user participation, so we only evaluate the user bonus. As shown in Fig. 6 that the benefits obtained by the two tasks are similar for each user. However, the total number of bonuses in $Task_2$ is much less than the total number of bonuses in $Task_1$. Figure 7 shows the average bonus and number of participants for $Task_1$ and $Task_2$ users. $Task_1$ has more bonuses than $Task_2$, but $Task_1$ has fewer participants than $Task_2$. It can be seen that the more participants, the better the incentive effect, the more the number of bonuses can be reduced.

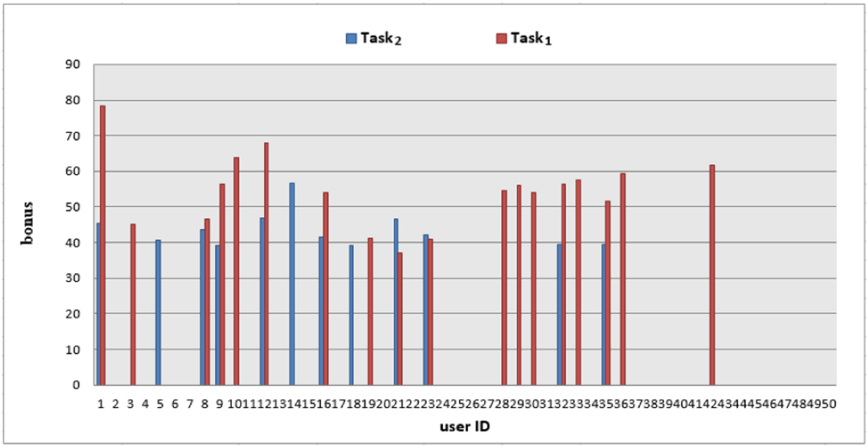


Fig. 6. Bonus analysis.

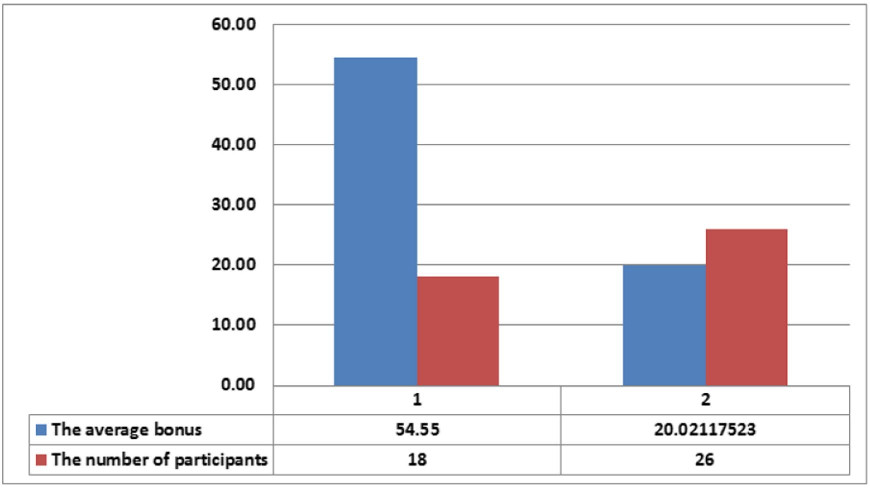


Fig. 7. The average bonus & number of participants.

5 Conclusion and Future Work

In general, reverse auction incentive mechanism based on the participant's behavior proposed in this paper has certain effects on user incentives. The current experiment is mainly based on the data set. Then we will collect the data in the field for experimentation and add the contrast experiment to reflect the excitation effect.

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