International Journal of Engineering Research And Management (IJERM)
ISSN: 2349- 2058, Volume-06, Issue-05, May 2019

A New Mobile Crowd Sensing Data Upload Mechanism

Qiuju Guo，Chaopeng Jia

***Abstract*—With the rapid development of science and technology, the mobile devices which we use in daily lives have integrated more and more sensors and been able to replace some of the traditional sensors to collect data, which makes the mobile crowd-sensing network to become an academic research hot spot. The users selected by the sensing tasks of the mobile crowd-sensing network are mostly distributed densely and encountered frequently, and the performance efficiency of the sensing tasks is improved by utilizing the short range wireless communication (such as Bluetooth and Wi-Fi) with opportunistic transmission. Through the research and analysis of the data collection mechanism in the mobile crowd-sensing network and aimed at the deficiencies of the ecoSense mechanism on budget control and user incentive, we proposed a CoES mechanism. In this paper, we design compensation schemes for domestic users and control the budget through compensation ratio. In the aspect of user motivation, we design IOR user incentive mechanism. According to the amount of data uploaded by the user who act as a chance really and the information of device’s power, we analyze the cooperation workload and reward. Finally, we use SWIM data set for simulation experiments, the results show that our scheme compared with the direct-assignment scheme can effectively reduce the costs to 53%, compared with the ecoSense scheme can reduce 5% of the cost, and the efficiency increased with the increment of the amount of data.**

***Index Terms*—Crowd Sensing, Opportunistic transmission，Incentive mechanism**

I. INTRODUCTION

The rapid development of Internet of Things makes the requirement for sense information getting higher and higher, which brings many new challenges for sensor networks and the common tasks such as environmental monitoring and traffic data monitoring. These tasks have practical application values only if a large number of individuals with high quality sense information. Traditional sensing networks require specific scenarios for specific tasks to deploy sensors that will generate a large number of deployment and maintenance costs, it undoubtedly hinder the development of “Internet of Things”. In recent years, with the popularity of smart phones and a variety of mobile devices bring a new sensing model--mobile crowd sensing (MCS) [1].MCS combines crowd sourcing ideas with mobile sensing, It takes the ordinary user's mobile device as sensing unit and engage in conscious or unconscious collaboration through the network. Finally, The MCS network is formed to the publication of the task and data collection to accomplish large-scale and complex sensing tasks. MCS not only provides a new sensing model for the Internet of Things, but also brings a series of new challenges, it has gradually become a hot topic of academic research.

The most important difference between MCS network and the traditional sensing network is sensor of MCS network have the attributes of human mobility and selfishness, which makes the incentive of network nodes become particularly important. If there is not a reasonable incentive mechanism [2], first of all, it may difficult to attract enough users to participate in the perception task. Secondly, in the data collection phase, the data provided by users is likely with poor quality or false sense and it will seriously affect the perception of the task. In other words, the design of the incentive mechanism is the most important part of the whole crowd sensing network. Currently, most applications use cash or virtual goods to compensate and motivate users to reduce the user's attention to data, electricity, and time. In general, the consumption of data is one of the most important concerns of users, and the cost of compensation is often the largest part of the overall budget. That is to say, reducing the consumption of the task data can not only stimulate the users very well, but also greatly reduce the total budget of the task. Therefore, how to design data upload mechanism from the direction of data saving is an urgent problem in crowd sensing network.

In this paper, we try to solve the problem through the research and analysis of the existing achievements and the actual situation. First, we investigated the data rates of the three main domestic network operators, China Unicom and China Telecom and China Mobile, and found that the data scheme used by users can be roughly divided into the following two situations: 1) monthly package: this type of users pay a monthly fee for using 3G/4G network, such as 36￥/month for 560MB in Chinese Unicom package. 2) Pay on demand: the demand for data for users is not large, and the users pay the amount of data they used, such as China Mobile's charge of 0.29￥/MB. We designed a corresponding data compensation scheme for different types of users, which we will introduce in the following. Secondly, the users who participate in crowd sensing tasks are densely distributed in the city and the opportunity of their meeting may be frequent. Moreover, now the smart mobile devices generally have Bluetooth, Wi-Fi and other short distance wireless communication ability that allow users to transfer data when meeting. We call it as opportunistic transmission [3]. In the process of uploading sensing data, if there is a time interval between the data collection and data upload, users will have enough time to choose the way to upload such as by Wi-Fi or by chance transmission, which will greatly save the data consumption of sensing tasks. Finally, the crowd sensing network nodes we mentioned above have the characteristics of human, that is to say, the collaboration between nodes and opportunistic transmission will not be conducted automatically. But the

Manuscript received May 09, 2019

Qiuju Guo*，School of Computer Science and Technology, Tianjin Polytechnic University, Tianjin, 300387, China).
Chaopeng Jia, Industrial and Commercial Bank of China Xinxiang Branch, Xinxiang, 453000, China

enough interest is one driving force to promote users to cooperate. Therefore, we will design incentive mechanisms to promote collaboration among users.

Based on the above information, we design a new upload mechanism of mobile crowd sensing network, which we call as CoES mechanism. By analyzing various factors, the mechanism divides the users into two types and we design a reasonable incentive mechanism to encourage users to collaborate. At last, it can minimize the total data compensation budget of the task publisher. In the design process of the whole mechanism, there are two important difficulties.

（1）How to design a reasonable data compensation scheme?

Since different types of users have different data compensation schemes, the user should first be reasonably divided before determining the compensation scheme. It is one-sided to divide users according to the packages of data. Because if the scope of a user's daily activities is covered by Wi-Fi network, they would not be divided into this group that pay the amount as they used because the free network can serve as the opportunity relay. Therefore, our classification main according to the user's mode of movement and the amount of data. Since we divide the user types is before the mission, we cannot determine the users' mobile mode and sensing data when they do the mission. So we use the historical data to divide the users. Considering the data of packages of users, we plan to pay monthly users a certain percentage of the monthly cost as compensation and this compensation ratio threshold helpful to control budget. To the users pay the fee as they used, we will pay the all cost as they used for completing task.

（2）How to ensure the opportunistic transmission between users?

In real life, two users encounter time is very short, and it is difficult to complete the operation of data transmission in this short period of time. The CoES system is divided into two parts of client-side and server-side. The server-side is mainly responsible for task release, user classification, data collection and payment functions, and the client-side is responsible for part installed on the user's mobile device， which is used to organize and upload the sensing data. By this way, users only need to select the strategy to automatic upload data. In order to promote the users actively use opportunistic transmission to collaborate, we designed the POR incentive mechanism to reward the relay users for ensuring the enthusiasm of users to perform tasks and saving data consumption.

To sum up, this paper makes the following contributions:

(1) According to the data rate of the communication operators, minimizing the total data compensation cost of the task by the upload mechanism of crowd sensing network.

(2) Based on existing research, CoES data upload mechanism is designed and implemented. The IOR incentive mechanism is used to encourage the users' cooperative transmission, and the compensation proportion threshold is introduced to control the task budget.

(3) Using SWIM simulated data sets to evaluate our scheme, the results show that compared with direct allocation scheme our scheme can effectively reduce about 56% of the total data costs, and compared with the ecoSense scheme, ours can reduce 5% of the cost and the saving efficiency improves with the increase of the data.

II. RELATED WORK

In recent years, with the popularity of smart mobile devices mobile, crowd sensing is developing rapidly, and we can feel these changes from some applications we use in our daily life. The common applications like Amap, DiDi taxi and micro-blog sports use the relevant theoretical knowledge of crowd sensing network. These applications use different incentives to transfer users' focus from mobile phone consumption to the application of reward, and thus successfully completed the data collection. Like vouchers incentives of DiDi taxi, the social incentive of micro-blog sports. Only by paying attention to the user's general concern and solving the inconvenience in the user's task, can we successfully complete the task of collecting data.

At present, the research on crowd sensing networks can be broadly divided into the following two categories:

(1) Study on the practical application: study how to apply the crowd sensing theory to the reality, like the literature [4] design a context aware system, which push music to the drivers for reducing accident rate according to the data collected by crowd sensing network. The literature [5] applies such information to predict bus arrival time. The paper [6] [7] applies such information to environmental monitoring and noise monitoring respectively.

(2) Study on the incentive mechanism：This direction is the hot spot of crowd sourcing networks, mainly studies how to encourage users to participate in and complete the task, and this paper also belongs to such direction. The literature [8] developed an incentive mechanism base on quality driven auction (QDA) that use the quality of data to express users' utility value and a probability model is proposed in this paper to evaluate the reliability of user perception data. Literature [9-13] motivates users to participate in tasks through game theory and various auction mechanisms. The literature [14] considers the limitation of single task and the cooperation of multitask in real scenes. Based on Berg stark game, it proposed an incentive framework to simulate the interaction between the server and the users and put forward four kinds of incentive mechanism. In document [15], a comprehensive framework for crowd sensing network is proposed, which includes three parts: reverse auction, game verification and reputation updating. In document [16], a long-term incentive mechanism based on data quality is proposed. But there is a problem in the most of these studies that is the fees provided to stimulate users or users asked is often put forward before the task is completed. So the price is likely to lead to special distribution of some tasks and influence the sense task.

In recent, some researchers aim at the shortage of research in the aspect of cost analysis in the past and conduct a series of new studies. Tuo Yu [17] have proposed a data sharing system named INDAPSON and designed a RAP incentive mechanism that calculate the reward through the way of analyzing the data and power for stimulating users to participate in data sharing. In document [18] [19], the researchers motivate users from the energy saving perspective by designing different data upload mechanisms. A new upload framework called ecoSense was mentioned in the literature [20], of which the core idea is that analyze users' cost from the data consumption of 3G. And in this paper, the compensatory money based on users' cost in the completion of task is estimated by the perceptual data. But this paper has some shortcomings. First of all, the target users in this paper are mainly foreign users and the tariff plan are divided into two types of not limited and pay immediately. This is clearly not in line with the domestic situation. Secondly, the compensation pricing scheme is based on the data pricing scheme listed by operators. If the amount of perceived data is large, it will produce the huge cost and the original plan will be deficient in the budget control. In addition, this paper only use cash to compensate the cost users spend in completion task, but there is no compensation for the consumption in cooperative transmission, which will undoubtedly affect perception data collection. After analyzed deficits of budget control and incentives in EcoSense, we proposed an upload mechanism called CoES for domestic users according to domestic data rates. Moreover, we have used the compensation ratio threshold to control the budget and designed IOR incentive mechanism to improve users' collaboration.

In this paper, we need to use the mobile forecast model to predict the trajectory of the users and there have some related research in the domestic and abroad. In paper [21-23], researchers used Markov chain model to calculate the probability of moving objects in the grid mobile unit. In paper [24], the trends of vehicle moving in a short period of time was predicted by the Gauss mixture model. While these papers are most based on the next location prediction in a short period of time, our prediction is needed for long time period (e.g. a task cycle) move. Because the movement prediction is not the focus of our research, we directly use prediction method of mobile mode based on the Poisson distribution proposed in [25].

III. PROBLEM DESCRIPT

In crowd sensing experiment, perceptual tasks can be divided into real-time tasks and non-real time tasks according to their timeliness. Among them, the real-time sensing task refers to the sensing data collected by users should be immediately uploaded to the server. Such tasks are common used in data monitoring map application and it requires the user to constantly update real-time data. As shown in Figure 1 the sensing period is T_0, in the start time of a task t ($t<<T_0$), the data collected before t is uploaded and the users do not have time to use other way to upload. Non real time sensing task refers to long-term perception tasks, it does not need to the users upload data immediately. The users only need to periodically upload the collected data. And this type are common used in environmental analysis. As shown in Fig.1, the data D_0 adopt by users in the period of perception update in period of [t_0, t_0+s_0] ,and in the delay time of S_0 , users can have enough time to select the way of uploading data, by Wi-Fi or posted by other users.

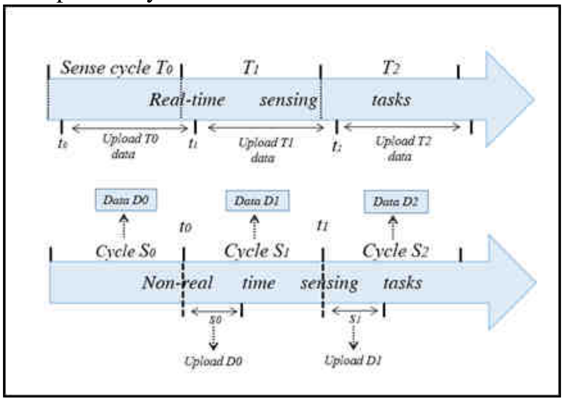

Fig. 1 Types of sensing task

The CoES data upload mechanism we designed is mainly for non-real time tasks. In the upload phase, we want users to upload data as much as possible using the free network. Before formally introducing the CoES mechanism, let's introduce several key definitions:

Definition 1 User Types: Division of users is the most critical part of the CoES mechanism. Only the reasonable classification of the users can we achieve the purpose of saving data through opportunistic transmission, and in this paper we will divided the users into two types.

① Users of DW (Data plan and Wi-Fi) :A user who has a data package and can often use free Wi-Fi is included in this group.

② NDW users: the users who use less data and are freely use free gateways in mobile mode. In this paper, the set of all users is U, $P(U) \rightarrow [U_D, U_N]$,, $U_D \cup U_N = \mathrm{U}$ and $U_D \cap U_N = \varphi$.

Definition 2 Upload Decision: In the stage of sensing data upload, users collect and organize the data of whole perception cycle $\mathrm{R_i}$. User N_i encounter with the free event e at the time t^* (t^*, [t_0, t_0+s_0]) and CoES will decide whether the data R_i need to be uploaded or transferred to relay. We use $D(Ni, R_i, t^*, e, t_0, s_0) \rightarrow \{true, false\}$ to represent this decision function. The upload strategy is the specific implementation of the upload policy. We use two upload strategies: *OneRelay*[19] and *UpEnd*[19]. *OneRelay* strategy refers to NDW users upload data by Wi-Fi or by transferring data to DW users in the relay time. And notice that the one times that users can use for transferring data to another in the use of *OneRelay* transmission strategy. *UpEnd* policy means that at the end of the delayed upload phase, the client-side will force users to upload all data to ensure that the data collected by the users is completely uploaded.Based on these definitions, we can get the objective function of total data budget (Data Compensate). Firstly, we must divide the whole users (P) into 2 types of DW and NDW, and for different types of users with different upload decision (D) and excitation mechanism (R). In constraint with these three factors, we strive to achieve the minimum budget, and the specific objective function as shown in formula 1.

$$\arg\min Budget_u = \arg\min(DC_{DW} + DC_{NDW} + \mathrm{Re}\,ward_U) \qquad (1)$$

$Budget_U$ refers to total budget，DC_{DW} and DC_{NDW} respectively refers to the data compensation of DW users and NDW users, $Reward_U$ refers to the fees of incentive mechanism.

IV. CoES MECHANISM

In order to solve the problem of objective function proposed above, we design a CoES data upload mechanism. In this part, we will firstly introduce the basic ideas in the mechanism, and then introduce the components and work data in the CoES mechanism.

For the users who execute non-real time sensing tasks under the CoES system, it is not necessary to immediately update data after collecting and they can choose a free method to upload in the delay time. The NDW users who cannot use the free Internet can upload data by opportunistic transmission when encountering with DW users. And one time transmission means that saving one cost of data. Of course, DW users will not freely help NDW users upload data, and the incentive mechanisms we designed are used to increase the opportunity of collaboration between users. The above is the basic idea of the CoES mechanism.

As shown in Fig.2, we can see that the CoES mechanism has three key components at run time: the incentive mechanism, user segmentation and upload decisions.

Incentive Mechanism: This part is mainly used to motivate users to use opportunity transmission to cooperate, which is the key in the implementation of the whole mechanism. In this paper, we will introduce the IOR incentive mechanism we designed in part 4.1.

User Partition: This part runs at the beginning of the first task cycle. The server divides the users into two types: DW and NDW. User segmentation is the basis for the implementation of the whole mechanism. In Chapter 4.2, the algorithm of user segmentation is introduced in detail.

Upload Decision: Upload decisions runs on the mobile device of users, which is used to decide whether the data should be uploaded or be transmitted to other users or be retained after the completion of collection. The upload strategy we have described in part 3 of the problem description.

By understanding the above information, let's briefly explain the work data of the CoES mechanism.

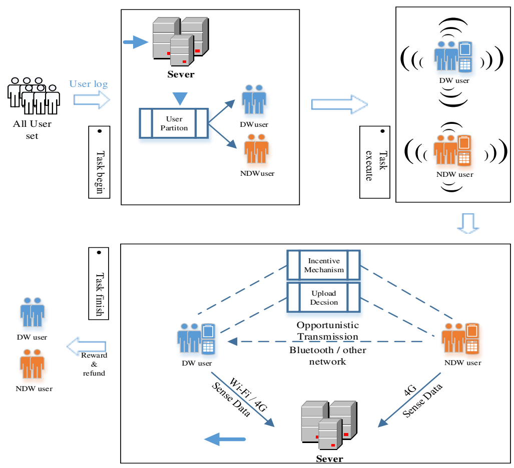

Fig.2 Mechanism framework of CoES

(1) At the beginning of the task, the part of user segment in server divides the users into DW and NDW according to the partitioning algorithm.

(2) During task execution, the user performs task of collecting sensing data.

(3) At the end of each task cycle, the users upload the data to the server. In the delay time, the part of upload strategy decide whether the data is transferred by chance transmission to other users or is directly uploaded to the server. The part of incentive mechanism records the user the opportunity cooperation between users for the payment of the incentive bonus. Finally, the server sends data compensation fees and incentive fees to users to keep users motivated.

4.1 DESIGN of INCENTIVE MECHANISM IOR

In the mobile crowd sensing network, sensing nodes owes the properties of mobility, sociability and selfish. The mechanism of CoES we designed does make full use of users’ mobility and sociability to conduct the opportunity transmission when the users encountering. However, selfish is an important characteristic of the user, the so-called selfish refers to the users for their own interests will choose not to carry out some cooperative activities. In our perception task, it can be represented as the behavior of refusing to help other users to transmit data or the activities of receiving other users’ data but not upload to the server. If this feature is ignored, the collection of perception data will be seriously affected. We design IOR (Incentive of Opportunistic Relays) incentive mechanism to encourage users to collaborate to transmit data and reduce the incidence of selfish behavior.

Under the mechanism of CoES, the upload strategy makes NDW users transfer data to the DW users for replacing the upload. As for the relay DW users, to upload more data means more data and power consumption, even the data is not the point for DW users, but the power is every user very concerned about. So we designed the IOR incentive mechanism from the aspects of equipment power, amount of sensing data and other considerations. The mathematical model as shown in formula (2).

$$\text{Reward}_{ij} = \frac{\Pr iceN}{1 + A * \varepsilon_{i,j}} * D_{i,j}, \varepsilon_{i,j} \in [0,1] \quad (2)$$

PriceN represents the unit price of NDW user data compensation，ε refers to the remaining power of users, D refers to the amount of transferred data, A is an normal number used for controlling the amount of bonus. The IOR incentive algorithm pseudo code is shown as algorithm 1, of which 2-4 lines are data processing to access to users’ information of transmission and electricity, the 5-9 line are for calculating incentive costs.

Algorithm 1：IOR Incentive Mechanism
1: *Input: PriceN,A*
2: *E←exchanges(U)*
3: *P←Power(U)*
4: *T←E,P*
5: *i,j←0*

```
for i<|U|
  for j<|C|
    read T
    Reward+=Reward
Output:Reward
```

4.2 USER PARTITION

User segmentation is the basis for the operation of the CoES mechanism, and the server reasonably divides the users into two types, DW and NDW, and finally achieves the goal of minimizing the total budget. The algorithm framework for User Partition is shown in Fig. 3.

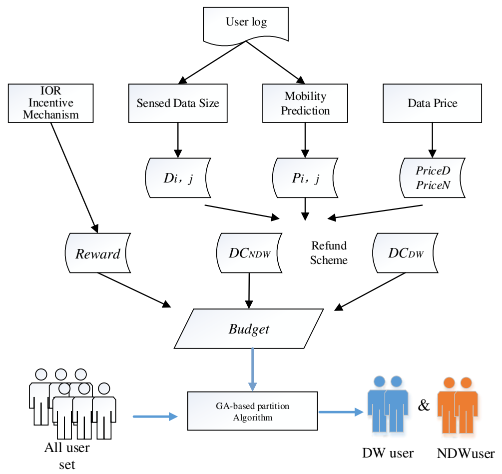

Fig. 3 Framework of User Partition algorithm

From this framework we can see that the key factors affecting the user division are the amount of sensing data and trajectory of users. Other data also has influence but not very obvious. Because the division of users is before the mission, we need to predict the amount of sensing data and the movement trajectory through the user history data of the last cycle.

(1) The amount of sensing data: According to the historical amount of sensing data in user log, we divide the tasks into fixed-size and varied-size with the amount of data task required. This amount of sensing data required by tasks are shown in formula (3).

$$D_{i,j} = \begin{cases} c & fixed-sizeSensedData \\ b + k * l_{i,j} & \text{varied} - sizeSensedData \end{cases} \tag{3}$$

$D_{i,j}$ represents the amount of data user i sensed in cycle j. In varied-size task, b refers to part of the integrating data inherent to each user, $l_{i,j}$ represents the unit amount of sensing data in the sensing location and k indicates the number of locations perceived.

(2) Trajectory prediction: Moving trajectories in this paper refers to the probability that the users use the free Wi-Fi or meet other DW users in the mobile mode. And the trajectory prediction is not the focus of our study. In this paper, the prediction method we used is based on Poisson distribution, and this method is so mature that can fully meet the needs of our experiment [14]. Moving trajectory prediction is shown in equation (4). The HS_j here represents the task time span (*Tstart, Tend, day_type*), and *#EVENTfree* (*Ui*, HS_j) indicates the number of free events triggered within the time span of HS_j.

$$\mathrm{P}_{i,j} = 1 - e^{\frac{-\#EVENT_{free}(U_i HS_j)}{|HS_j|}} \tag{4}$$

Through the above two kinds of information and Tariff Scheme of operators, we can initially determine the DW users and NDW users data compensation scheme.

For DW users, we compensate for part of their monthly package costs. If their data exceeds the standard and is used for sensing tasks, we will compensate them for excess data. The compensation scheme is shown in equation 5.

$$\mathrm{DC}_{DW} = M * \mathrm{Price}D + q * \mathrm{PriceN} \tag{5}$$

Among them, M indicates that the compensation ratio for DW users. q refers to the exceed data of the package, and we use m_i to express the compensation ratio threshold of the user i, which is related with whether the user is willing to do the task and is proportional to their willingness to cooperate. In this paper, the function $Ji=f(m_i, M)$ is used to indicate willingness to participate. As shown in equation 6.

$$\mathrm{J}_i = \begin{cases} 1, & \mathrm{m_i} \le \mathrm{M} \le 1 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

For NDW users, we compensate all the data costs used to perceive tasks, and the compensation scheme is shown in equation 7.

$$\mathrm{DC}_{NDW} = \mathrm{D_{i,j}} * (1 - \mathrm{P_{i,j}}) * \mathrm{PriceN} \tag{7}$$

To sum up, we can obtain the final objective function of the partitioning algorithm, as shown in equation8.

$$\begin{aligned} Budget_U &= DC_{DW} + DC_{NDW} + \mathrm{Reward}_U \\ &= (|\mathrm{U}_{DW}| * M * PriceN + \sum_{k \in U_D} q_k * \mathrm{PriceN}) \\ &+ \sum_{l \in U_p}^{j \in C} D_{i,j} * (1 - P_{i,j}) * PriceN \\ &+ \sum_{i \in U}^{j \in C} \frac{PriceN}{1 + A * \varepsilon_{i,j}} * d_{i,j} \end{aligned} \tag{8}$$

Considering that user segmentation can lead to a variety of complex problems, we use a genetic algorithm to get the optimal partition, and the pseudo code of the algorithm is shown in algorithm 2.

```
Algorithm 2: GA-based Patition Algorithm
Input: Budget , U
Output: U_DW, U_NDW, Budget
  B ← bivector (U)
  N (population) ← B
  i ← 0
  while i < iter_max do
  K ← keepbest (N)
  C ← crossover (N)
  M ← mutation (N)
  N ← {K,C,M}
  i ← i + 1
  end while
  output :U_DW, U_NDW, Budget
```

V. THE EVALUATION OF SIMULATION EXPERIMENT

The language environment of the simulation experiment is

Python2.7 under the Windows XP system, including DEAP [26], SciPy scientific computing, Matplotlib scientific map and other components. The data set used in the simulation experiment is SWIM[27] simulation data set, and 48 objects with complete data are extracted as simulation objects to effectively evaluate the CoES data upload mechanism.

We have investigated the most widely used data pricing schemes for mobile, China Unicom and Telecom, as shown in table 1. Due to influence of the standard tariff on the trend of experimental data is not great, we only adopt China Unicom tariff standards in the simulation experiment to make the compensation scheme. Because the content of package involves calls, text messages and calls to display, our experiment refers the basic standard of compensation for DW users as 30 yuan/month.

Table1 Data plan of 3 operators

Operator	data plan	DP rate	No DP rate
Mobile	500MB	58Yuan/month	0.29Yuan/MB
China uniform	500MB	36Yuan/month	0.3Yuan/MB
Telecom	1000MB	50Yuan/month	0.3Yuan/MB

We have used the following two schemes to compare with the CoES mechanism:(1) Direct allocation scheme: this scheme simply defines them as DW types or NDW types based on the amount of data perceived by the user; (2)ecoSense scheme: The scheme simply compensate to the users for the data consumed by the crowd sensing task.

(1) The quantitative sensing data: in this experiment we assume that the amount of data required by task in each cycle is certain, we tested the change of total budget in the data amount of 1000KB-6000KB/cycle, and compared with the direct allocation scheme, CoES can save the cost of 35%-55%. Compared with the ecoSense scheme, CoES can save about 7% of the cost. We found that when the amount of data is at 3500KB/ cycle, the saving effect is most significant compared with the direct allocation scheme. The main reason for this is that the direct allocation scheme define all users as the DW type, and with the increase of data quantity, the saving effect of ecoSense will be more obvious, which indicates that the IOR excitation has a better effect to the direct compensation. The experimental data are shown in Fig. 4.

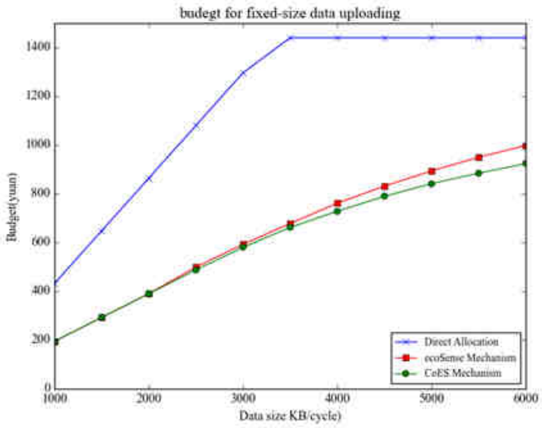

Fig. 4 Fixed-size task budget of sensing data

(2) Non quantitative sensing data: now we consider data costs of non-quantitative task. In the experiment, we consider two cases of C = 0 and c≠0 in the formula $d_{i,j}=c+k*l_{i,j}$. In this experiment, we set the unit element K of each access base station in 100+1000KB/station and test the total budget change.

①When c=0, we assume that the user only upload their own sensing data in their access location. The result of experiment show in Fig.5.In Fig.5, we can find CoES could save the cost of 30%-50% compared to the direct allocation, and 1%-10% to the EcoSense.

We can see that with the value of K increases, the saving efficiency is increased. That's the reason people prefer choosing opportunistic really users to upload data.

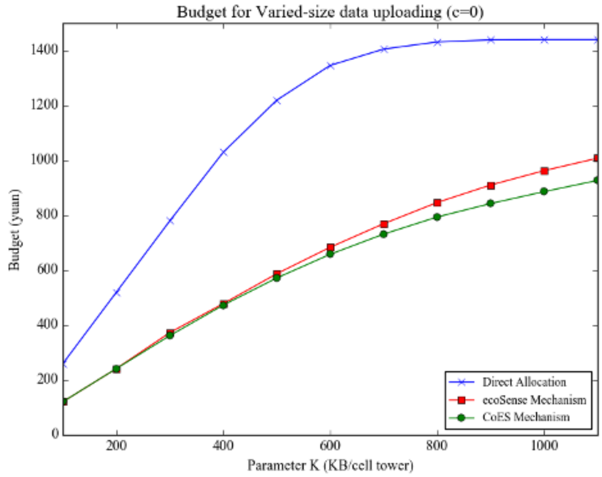

Fig.5 Varied-size task budget for sensing data（c=0）

②When c≠0, we assume that users not only upload their access location data but also some other data such as activities log data. We assume this part of data is 500KB. The result of experiment shows in Fig.6. In the Fig.6, we can find the overall trend is similar as Fig.5. CoES could save the cost of 37%-54% compared to the direct allocation and 1%-10% to the EcoSense. But each value of K would higher than Fig.5, this is caused by the value of c.

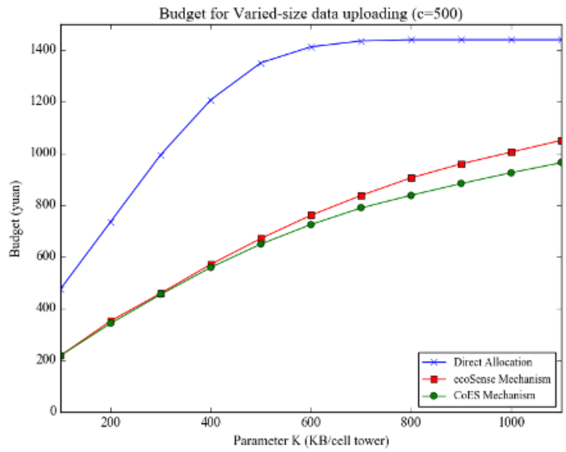

Fig. 6 Varied-size task budget for sensing data（c=500）

(2) Different proportion of compensation: in previous experiments, the proportion of compensation is set at M=0.8. But in this experiment we discuss the cost of different proportion of compensation under the CoES. Before this experiment, we surveyed 400 monthly users who were willing to participate in sense tasks in different proportion of compensation in the form of a questionnaire. The statistics are shown in table 2. We can see that participation rate of users higher when the proportion in 0.7-0.9. When M=1.0, the user participation rate is highest at M = 1.0, but in this time, budget would overrun. Therefore, we set M = 0.8 in our experiment, both the user participation rate and the task budget are well controlled.

Table2 User participation rate statistics

Compensation ratio M	Number of participants （Total number 400）	Participation rate
0.4	78	19.5%
0.5	136	34%
0.6	187	46%
0.7	248	61.3%
0.8	312	78%
0.9	322	80.5%
1.0	387	96.8%

In this experiment, we set the amount of sense data in 4000KB/cycle. The result of experiment shown in Fig.7. The saving efficiency increases with the compensation proportion decrease. In the figure when the red line is M =0.75, this point is the least scale value ensure the user participant rate over 65%, But proportion of compensation directly influence user's willing of participant which should be set carefully.

(3) IOR incentive mechanism: in this experiment, we tested the user's reward within one month when the amount of data perceived by each cycle was 4000KB and 6000KB, the experimental data is shown in Fig.8. We can see from Fig.8 that when the data quantity is 4000KB/cycle, only the three users of NO.1, No. 21 and No. 22 have won the collaboration awards, and in the amount of data is 6000KB/cycle, the users of 1-5, 21-25, 41 and 43-45 are rewarded. It is obvious that when the amount of data is small, many users would help upload data. For the CoES mechanism, when the amount of data is small, the compensation would not consume too much. As the increase of data quantity, the reward users got is also increase, which proves the opportunity of transferring data between users also improves.

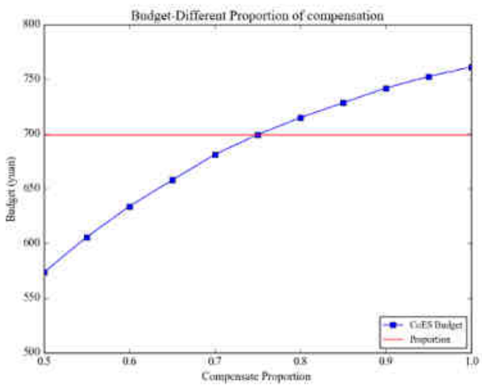

Fig.7 Comparison of different compensation ratio

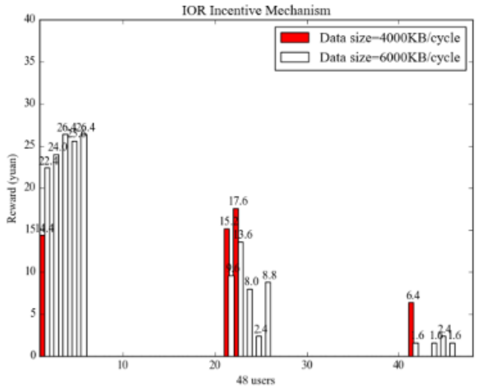

Fig.8 IOR incentive mechanism

VI. CONCLUSION

In view of the deficiency of ecoSense crowd sensing data upload mechanism, CoES mechanism based on IOR incentive model is proposed in this paper. The mechanism divides users into different types and uses the IOR incentive model to motivate users who act as opportunity relays, and performs well in both budget control and user incentives. In future work, we will further improve the mechanism. In this paper, the way we used to motivate users is cash, but there are many incentives for our reference, such as vouchers, virtual goods and integral level other kinds of incentive methods. Moreover, the user's power consumption is also an important factor for influencing participation of crowd sensing tasks, and we will do more in this aspect.

REFERENCES

[1] RK Ganti, F Ye. and H Lei. Mobile crowdsensing: current state and future challenges. Communications Magazine IEEE, 2011,49(11),pp.32-39.

[2] Wu Y., Zeng JR Peng H, Chen H, Li CP.Survey on incentive mechanisms for crowd sensing. Ruan Jian Xue Bao/Journal of Software, 2016,pp.2025-2047.

[3] Ma H, Zhao D, Yuan P. Opportunities in mobile crowd sensing, IEEE Communications Magazine,2014, 52(8),pp.29-35.

[4] Krishnan A S, Hu X, Deng J. et al.(2015). A Novel Cloud-Based Crowd Sensing Approach to Context-Aware Music Mood-Mapping for Drivers. IEEE, International Conference on Cloud Computing Technology and Science,2015, pp. 475-478.

[5] Biagioni J,Gerlich T, Merrifield T. et al. EasyTracker: automatic transit tracking, mapping, and arrival time prediction using smartphones. International Conference on Embedded Networked Sensor Systems,2011,pp. 68-81.

[6] Dutta P, Aoki P M, Kumar N. et al.Common Sense: participatory urban sensing using a network of handheld air quality monitors. International Conference on Embedded Networked Sensor Systems,2009,pp. 349-350.

[7] Rana R K, Chou C T, Kanhere S S, et al.Ear-phone: an end-to-end participatory urban noise mapping system. ACM/IEEE International Conference on Information Processing in Sensor Networks, 2010,pp. 105-116.

[8] Wen Y, Shi J, Zhang Q. Quality-Driven Auction-Based Incentive Mechanism for Mobile Crowd Sensing. IEEE Transactions on Vehicular Technology,2015,64(9), pp.4203-4214.

[9] Ma P, Tao D. "5W1H" model for incentive mechanism in mobile crowd sensing. IEEE International Conference on Consumer Electronics-Taiwan,2016,pp. 1-2.

[10] Zhu X, Jian A, Ywang M. et al . A Fair Incentive Mechanism for Crowd sourcing in Crowd Sensing. IEEE Internet of Things Journal,2016，3(6),pp. 1-1.

[11] Zhao D, Li X Y, Ma H. Budget-Feasible Online Incentive Mechanisms for Crowdsourcing Tasks Truthfully. IEEE/ACM Transactions on Networking.2014, 24(2),pp. 647-661.
[12] Zhao D, Ma H, Liu L. Frugal Online Incentive Mechanisms for Mobile Crowd Sensing.IEEE Transactions on Vehicular Technology.2016,66(4),pp. 3319-3330.
[13] Huang L, Zhu Y,Yu J. et al. Group Buying Based Incentive Mechanism for Mobile Crowd Sensing. IEEE International Conference on Sensing, Communication, and Networking.2016,pp. 333-341.
[14] Luo S, Sun Y, Ji Y. et al. Stackelberg Game Based Incentive Mechanisms for Multiple Collaborative Tasks in Mobile Crowdsourcing. Mobile Networks and Applications.2016,21(3), pp.506-522.
[15] Dai W, Wang Y, Jin Q.et al. An Integrated Incentive Framework for Mobile Crowdsourced Sensing. Tsinghua Science and Technology.2016,21(2), pp.146-156.
[16] Sun J. Marginal quality - based long - term incentive mechanisms for crowd sensing. International Journal of Communication Systems. 2015,29(5), pp.942-958.
[17] Yu T, Zhou Z, Zhang D.et al. INDAPSON: An incentive data plan sharing system based on self-organizing network. Proceedings - IEEE INFOCOM.2014, pp.1545-1553.
[18] Chen L, Wang L, Zhang D.et al. EnUp: Energy-Efficient Data Uploading for Mobile Crowd Sensing Applications. International Workshop on Crowd Intelligence for Smart Cities: Technology and Applications.2016,pp. 1074-1078.
[19] Wang L,Zhang D,Xiong H. effSense: energy-efficient and cost-effective data uploading in mobile crowdsensing. ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication. 2013,pp. 1075-1086.
[20] Wang L, Zhang D, Xiong H. et al. EcoSense: Minimize Participants' Total 3G Data Cost in Mobile Crowdsensing Using Opportunistic Relays. IEEE Transactions on Systems Man & Cybernetics Systems. 2016,pp. 1-14.
[21] Ishikawa Y, Tsukamoto Y, Kitagawa H. Extracting Mobility Statistics from Indexed Spatio-Temporal Datasets. Spatio-Temporal Database Management. 2004, pp. 9-16.
[22] Song M B, Ryu J H,Lee S K.et al. Considering mobility patterns in moving objects database. International Conference on Parallel Processing. 2003,pp. 597-604.
[23] Qiao S, Shen D, Wang X.et al. A Self-Adaptive Parameter Selection Trajectory Prediction Approach via Hidden Markov Models. IEEE Transactions on Intelligent Transportation Systems. 2015,16(1), pp.284-296.
[24] Wiest J, Hoffken M, Kresel U. et al. Probabilistic trajectory prediction with Gaussian mixture models. IEEE Intelligent Vehicles Symposium. 2012, pp. 141-146.
[25] Chon Y, Shin H, Talipov E. et al.Evaluating mobility models for temporal prediction with high- granularity mobility data. Pervasive Computing and Communications (Per Com). 2012,pp. 206-212.
[26] De Rainville F M, Fortin F A, Gardner M A. et al. DEAP: A Python framework for Evolutionary Algorithms. Genetic and Evolutionary Computation Conference Companion.2012,pp.85-92.
[27] Kosta S, Mei A, Stefa J. Large-Scale Synthetic Social Mobile Networks with SWIM. IEEE Transactions on Mobile Computing. 2014,13(1), pp.116-129.