QUOIN: Incentive Mechanisms for Crowd Sensing Networks

QUOIN: Incentive Mechanisms for Crowd Sensing Networks

Kaoru Ota, Mianxiong Dong, Jinsong Gui, Anfeng Liu

Abstract: Crowd sensing networks play a critical role in big data generation where a large number of mobile devices collect various kinds of data with large-volume features. Although what information should be collected is essential for the success of crowd-sensing applications, few research efforts have been made so far. On the other hand, an efficient incentive mechanism is required to encourage all crowd-sensing participants including data collectors, service providers, and service consumers to join the networks. In this article, we propose a new incentive mechanism called QUOIN, which simultaneously ensures Quality and Usability Of INformation for crowd-sensing application requirements. We apply a Stackelberg game model to the proposed mechanism to guarantee each participant achieves a satisfactory level of profits. Performance of QUOIN is evaluated with a case study and experimental results demonstrate that it is efficient and effective to collect valuable information for crowd-sensing applications.

Introduction

Crowd-sourced data is gathered from people with various types of sensors on mobile devices, e.g., GPS, accelerometer and camera, and is considered supplement of or even alternative to traditional data sources [1-3]. With proliferation of the mobile devices and advanced sensing technologies, crowd sensing networks generate a massive volume of mobile sensing data, so-called mobile big data. The mobile big data contains useful information for several purposes and there are two key factors for success of crowd-sensing applications: quality and usability of the information. First, the quality of information is quality of data collected from Data Collectors (DCs) by Service Provider (SP) standards, which includes data validity (i.e., degree of validity for perception scene reflected by the provided data), data timeliness (i.e. the time stamp of the data is within a certain period of time), and so on. Second, the usability of information is how much information useful for Service Consumers (SCs) is contained in the provided data, which includes data quantity (i.e., the amount of information contained in a unit capacity), data coverage (i.e., the ratio of the area covered by already collected data to a whole perception area), and so on. Requirements on those information characteristics depend on target applications emerged with explosion of mobile sensing data, social networking, and cyber-physical systems.

There are several examples for such application scenarios. Waze [4] is a community-based traffic and navigation application where drivers can share real-time traffic and road information in a city with other drivers. People can save time and reduce fuel costs on their daily commutes with Waze. Weather-Lah [5] is an application of Singapore weather forecast that aims at providing users with more accurate and real-time weather information with crowd-sourced data. Real-time alerts are sent out to inform users that it is going to rain, flood, and other special weather. From the practical point of view, not only the quality of information, but also the usability of information is needed for those applications. For example, SPs collects high-quality of information but information of some area is still missing, which cannot ensure the collected data covers the entire expected perceptual area. Application users may be not able to fully enjoy benefits of the applications, e.g., saving time and fuel costs for Waze, even if only a small amount of information lacks. Mana Rapid Transit [6] is an iPhone app where users answer a simple question whether it is crowded around them or not at the present time. Based on submission of the users, it shows a result of crowdedness in the Mass Rapid Transit (MRT) subway stations and trains. If such a system can be successfully applied in our daily lives in the early, the tragedy of waterfront area of Shanghai can be avoided, which killed at least 36 people and injured 47 when occurred shortly before midnight, at 11:35 p.m. December 31, 2014 in the stampede incident. Thus, outdated data not only hinders provision of high quality service but also may mislead users, or even worse, it will cause serious loss for applications.

Kaoru Ota and Mianxiong Dong are with Department of Information and Electronic Engineering, Muroran Institute of Technology, Japan.
Jinsong Gui and Anfeng Liu are with School of Information Science and Engineering, Central South University, China.

However, it is challenging to ensure the quality and usability of information in crowd sensing networks. DCs need to consume resources (e.g., power, bandwidth, traffic cost, time, and equipment) in order to sense and collet data. Therefore, most DCs are not willing to contribute if the cost is not reasonable and affordable. SPs collect data from DCs while paying a certain amount of payment to DCs as rewards. Then, SPs composite the collected data and provide SCs with Advanced Services (ASs) to reap benefits from a charge for use of ASs. Therefore, without any incentive mechanism, it will be difficult to collect quality and useable data which meets application requirements to satisfy SCs [7-10]. SPs will not be able to expect much income from SCs and to give DCs strong incentive for data collection without fat budget. Most of DCs will lose their motivation to provide sensed data, and thus it further decreases the effectiveness of applications. Eventually it leads to death of the crowd-sensing network [8, 9].

Some of SPs need only the minimum set of data to ensure the data coverage of the sensing area. Generally speaking, it is easier to collect high volume of data in an urban-city area than a rural one because a lot of people and devices can sense the surrounding environment. Also, people can submit collected data at almost anywhere and anytime without stress for accessing to the Internet in the urban-city area. However, enormous quantity of collected data is not always good from two points of view. From perspective of SPs, too much data increases wasteful expenditure because it may include much redundant data that SPs need to make extra payment for. Too much data also leads to ineffectiveness of operating applications. In many applications like Waze and Weather-Lah, the sensing area is divided into a unit grid where the data coverage is determined by the grid. If a certain amount of data is submitted by DCs to a grid, the data coverage is satisfied at the grid. Thus, some information is useless for SPs because of increasing the burden for operating applications without any expected profit. From perspective of network operators, the redundant data will increase network loads and thus reduce the network performance.

Although many incentive mechanisms or techniques have already been proposed or developed, they are inadequate for emerging big data scenarios to satisfy all crowd-sensing participants: DCs, SPs, and SCs. In this article, we devote our attention toward an incentive mechanism efficient for all the participants to collect the quality and usable information in crowd sensing networks. First, we give a general architecture for big data collection and its application for crowd sensing networks, and then review some existing incentive mechanisms/techniques proposed in the literature. We propose a market-based incentive mechanism called QUOIN under certain pricing principles as a case study. Finally, we draw conclusions and discuss some future research directions.

Architecture and incentive requirements in crowd sensing networks

We present a general architecture for big data collection and its applications in crowd sensing networks and identify requirements for designing effective incentive mechanisms.

Architecture for big data collection

Figure 1 shows a general architecture to collect big data and provide services in crowd sensing networks, which is mainly composed of three parts: hierarchical big data collection, service compositing and providing, and application or service consumption.

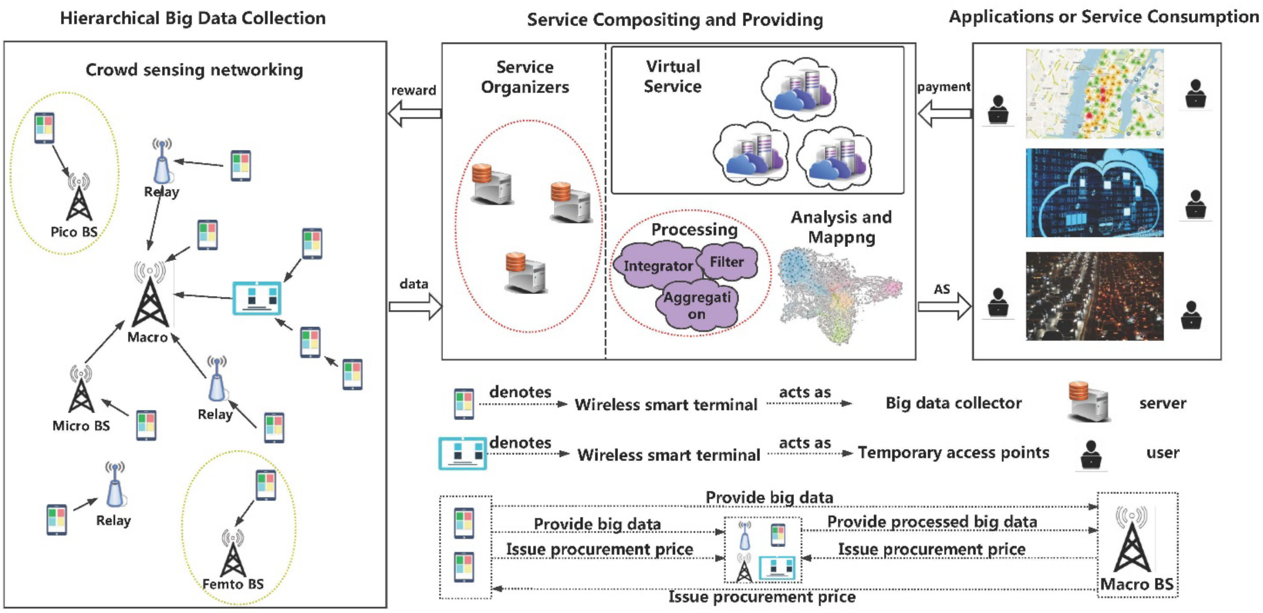

Figure 1. General architecture of big data collection in crowd sensing network

(1) Hierarchical Big Data Collection.

Wireless smart terminals are the most extensive and basic DCs in crowd sensing networks. The left part in Figure 1 shows distribution of the wireless smart terminals in actual network environments. Data sensed by the wireless smart terminals can be submitted to the DCs via access to Macro Base Stations. Data submission can also be possible through LAPs (Little Access Points) (e.g., Micro Base Stations, Pico Base Stations, Femto Base Stations, relay stations deployed by operators) in areas adjacent to the DCs. Such a diversified submission mode can effectively deal with challenges brought by big data features (e.g., multi-source, pervasive, heterogeneity). At the LAPs, not only big data is received from nearby DCs, but also it should be appropriately handled (e.g., filtering, cleaning, fusion, aggregation) for submission to the DCs, which can reach a goal that the collected big data is high enough to be "graded" [1, 8].

The distributed and diversified submission mode can also balance the load for big data collection, and thus ensure the data timeliness for big data. Due to the consideration for investment costs, the LAPs deployed by operators are always limited, and forecasting deployment positions for these LAPs is not always accurate. Thus, it is hard to reach the desired sensing coverage. In a temporary "hotspot" areas, if a large number of sensing devices cannot find any LAP in near them, they have to send their sensed data to the single Macro Base Station through competition for accessing a channel. That results in congestion at a single access point, which not only seriously affects the data timeliness but also significantly increases cost (e.g., energy) of big data collection. Although some existing works have been proposed on congestion control and transmission delay [11,12], new solutions for the hotspot problem in crowd sensing are required. To this end, energetic devices at adequate positions among numerous wireless smart terminals become temporary relay stations as delegates to send data collected by other devices to the LAPs. This can solve a blind zone problem caused by a shortage of the LAPs and thus improve the data coverage of desired perceptual regions.

(2) Service Compositing and Providing.

Crowd-sensing networks include usually multiple SPs, which provide weather forecast service, traffic information service, real-time service, and so on. Even one service can be provided by multiple SPs. As shown in the middle of the upper part in Figure 1, big data is collected over distributed and different types of terminals and is submitted to all kinds of SPs for compositing all kinds of ASs after certain processes (e.g., filtering, refining, analyzing, mapping, integrating). ASs can be composed in both a centralized and a hierarchical manner. Low-level servers for composing ASs can be deployed in both regions near LAPs and the core area of infrastructure, while high-level servers can usually be deployed in the core area of infrastructure.

(3) Application or Service Consumption.

Once SPs release ASs, SCs can select services to meet their needs. The right side of the upper part in Figure 1 shows ASs for SCs. SCs can use multiple services from a given SP, and also use the same type of service from multiple SPs. Meanwhile, a single SP can provide the same type of service, and also provide different types of services.

Requirements for effective incentive mechanisms

Subjects of crowd sensing (i.e., DCs) belong to different autonomous entities and are not controlled by a single administrator. Therefore, it is more reasonable in this case to assume that the subjects are selfish and can act in their self-interest. To effectively collect quality and usable data from DCs and provide high quality services to SCs, it is necessary to design a reasonable incentive mechanism to balance among the load coming from big data collection, to stimulate network vitality, and to maximize network benefit.

Big data collection is the same as the traditional data collection where it costs resources of DCs (e.g., energy, processing time and the storage unit, channel bandwidth). In crowd sensing networks, the main body (i.e., DCs) belongs to different individuals or social groups, etc. If the incentive mechanism is not enough attractive, it is difficult to guarantee that a large number of participants join in activities of perception and big data collection. Big data collection faces a bigger challenge than traditional data collection. For example, traditional data collection requires that DCs have an ability to adapt to diverse types of data, an ability to avoid or to reduce redundant data, an ability to cooperate among other collectors, and so on. Most existing incentive mechanisms cannot motivate participants to improve such abilities of theirs; thus, it is difficult to motivate DCs to participate in the activities of big data collection that guarantees quality and usable data. Based on the general architecture for big data collection as shown in Figure 1, requirements for designing effective incentive mechanisms are listed as follows.

(1) Requirement in distributed big data collection.

In a populated area, a critical ability of a DC is to coordinate cooperation of data collection where each DC plays their own special skill, e.g., a DC can sense multiple kinds of sensory data simultaneously while another DC has much energy to sense high quality and volume of data. Cooperation can make up for a limited individual ability each other. On the other hand, it can also help to avoid or reduce redundant data while ensuring that collected data is enough quality and usable; it can effectively reduce the cost of collecting data. In such a scenario, the first requirement is to stimulate DCs to fully utilize an "individual combat capability" of DCs.

(2) Requirement in hierarchical big data collection.

In big data collection, hierarchical deployment of access points can avoid single point congestion, which contributes to improve the data timeliness and the data coverage. Because of expensive setup costs, it is not a reasonable solution that access points are pervasively and densely deployed. An alternative solution is that some DCs act as a temporary relay station; however, if there is no incentive mechanism, nobody wants to “sacrifice” precious resources such as energy and memory of wireless intelligent terminals. Thus, the second requirement is to simulate DCs to be a temporary relay station to overcome a "blind spots" problem.

(3) Requirement for network equilibrium.

Due to big data features: high volume and distributed multi-sources, it is crucial to balance data flow between data collecting points and network access points, which makes full use of network resources. If DCs try to participate in a game to get an access to a base station, it could be fail to collect some important data because a DC who has that data may lose the game. Thus, the third requirement is to prevent DCs from competing with others in a densely populated area by giving good incentives, which helps to balance the network load and to efficiently use resources to improve the quality and usability of collected data.

(4) Requirement for network vitality.

The big data collection requires involving as many as DCs and their active cooperation in essence. However, in terms of environmental perception, a huge number of individual DCs will cause unnecessary loss of resources and much redundant information. Therefore, the incentive mechanism should consider mining value of big data that shows how much it contributes to constructing value-added services in a condition of limited cost for data collection, and then consider rewards to the DCs. The forth requirement is to prompt network members (i.e., SPs and DCs) to follow principles of collecting the data from "good" nodes and avoiding the "bad" nodes.

Based on the above four requirements, we give principles to design the incentive mechanism in crowd sensing networks as follows. (a) If subjects know that SPs give a very low procurement price for low quality and usable data, they will not collect such data. (b) If subjects know that a number of DCs participates in crowd sensing, they will evaluate their own abilities to determine whether to participate or not. Voluntary withdrawal of subjects with low ability can reduce unnecessary channel competition and thus improve the timeliness of big data collection. (c) If subjects know that the number of DCs is small in a desired perceptual region, they will be more active to participate in big data sensing and provide rare data. (d) If subjects know that they are in blind spots without LAPs near them, they will actively apply for acting as temporary relay stations, and thus improve the perceived coverage of a desired perceptual region.

We will design the effective incentive mechanism based on those principles by means of the Stackelberg game model.

Existing incentive mechanisms

In the aspect of crowd sensing, researches on incentive mechanisms have just started. In [7], Yang et al. design two incentive mechanisms based on auction, namely platform-centered and user-centered, to motivate smart phone users to involve in perception and complete perception task. In [8], J. S. Lee et al. propose a reverse auction mechanism, which allows users to publish their expected value to SPs where SPs are glad to buy their data. In [9], T. Luo et al. propose an incentive mechanism, which stimulates participation of users to the game. This mechanism pays full payments for an SP and sets reward according to contribution of auction. The works in [7-9] only consider an interaction between SPs and DCs, but does not take into account the act of payment consumption of SCs. The work in [10] can solve this problem; therefore, their proposed scheme can achieve goals that an SP gains profit by collecting data to construct value-added services. It can reach a market equilibrium (market equilibrium), namely maximizing utility of DCs and SC. However, all of the above works do not consider competition among service organizers (i.e. SPs). Although the works in [13, 14] describe the service price competition relationship among organizers and point out that this competition will eventually reach balance, it does not describe a price competition relationship among DCs. In this article, we fully consider a price competition relationship between SPs and DCs, SPs and SCs, as well as among SPs, DCs and SCs.

Incentive mechanism for crowd sensing networks

We propose the incentive mechanism for crowd sensing networks called QUOIN and apply the Stackelberg game model based on multi-master multi-slave structure to QUOIN. In this game model, SPs are leaders [15], and represented as a set: SP={SP_1, SP_2, …, SP_m}; DCs and SCs are followers, and respectively represented as set: DC={DC_1, DC_2, …, DC_n} and set: SC={SC_1, SC_2, …, SC_g}. The interaction between the leader (i.e., SP) and followers (i.e., DC and SC) is described in Figure 2.

(1) The leader: SP

An SP collects data from DCs through paying a certain reward to DCs, and then composites those to ASs. The SP provides ASs to SCs, and gets benefits by receiving payments. The utility of the SP is the difference between received benefits and cost for collecting data. Thus, we can obtain a utility function using the price for each service provided by the SP, the number of SCs which use the services from the SP, the price for buying data from DCs, and the number of data provided by DCs. Generally, the more the number of SPs, the lower a service price from SP. If the price is very low, profits may be reduced whatever the number of services is, so that each SP must choose a suitable price for collecting data. In the utility function, we define the most important incentive parameter ξ to guarantee collecting quality and usable data. The incentive parameter can be adjusted by SPs based on their own pricing principles. In this article, the following pricing principles are considered as an example: (a) If the data validity is high, the purchasing price is high; (b) If the data timelines is high, the purchasing price is high; (c) The more DCs provide similar data, the lower purchasing price; (d) If the collected data is more important on data coverage, the price is higher. For optimal pricing for SP, we seek the maximum gain of the utility function with consideration of an optimal price strategy, service requirements, and a data collection strategy selected by other participants to satisfy their own utility.

(2) The follower: DC

A DC decides the following two points: "what data should be collected?" and "which SP should be selected to provide the collected data according to a purchasing price for different SPs and a cost of collecting data." The utility function of the DC is composed of the price when the DC collects data for a certain SP, the total number of the SP's services used by SCs, and the number of collected data which is determined by expected profits according to the first two parameters. A goal of the DC is to maximize its own utility function while considering an optimal price strategy, service requirements, and a data collection strategy selected by other participants in the game (including the SP and the DC).

(3) The follower: SC

An SC is a demander of ASs. The utility function of the SC means a received profit which can be obtained by the number of used services of a certain SP and the price for the use of each service. A goal of the SC is to maximize its own utility function while considering an optimal pricing strategy and a service strategy selected by the other participants in the game (including the SP and the SC).

(4) Reach the optimum for every participant

An SP, an SC, and a DC play a game through a price incentive mechanism. The SP keeps the purchasing price after the SP sets a price for each service and incentive parameter ξ. The SC and the DC respectively adjust their own service consumption and data collection strategy to make the system reach steady state. The price of each service of the SP is adjusted in interval Δt of iterations where each Δt contains multiple intervals $\Delta \tau$ which is adjustment time for parameters of the SC and the DC. At the final state, the SP, the SC, and the DC can obtain the optimal service pricing, data acquisition pricing, service demand, the amount of collected data, respectively. Then, the system reaches the Nash equilibrium state. The iterative process for the entire incentive game mechanism is shown in Table 1.

Table 1. Iterative process for the entire incentive game mechanism

Algorithm 1: The pseudo-code of QUOIN

```
Scenario
    Set Service Provider set SP={SP_1, SP_2, …, SP_m};
    Set Data Collector set DC={DC_1, DC_2, …, DC_n};
    Set Service Consumer set SC={SC_1, SC_2, …, SC_g};
    Initialization
        Initialize value of profits with a data collection strategy and incentive parameter ξ for each DC
        Initialize value of profits with a service consumption strategy and the initial price of services for each SC
  Do while
            DO   While Any SP does not gain the maximum value of the utility function;
                For each moment t, each SP changes the price of services during the epoch Δt;
                    Each SC changes its service consumption strategy for each slot Δτ;
                    Each DC changes its data collection strategy for each slot Δτ;
                    t = t + 1;
                End For
        End do
End do
```

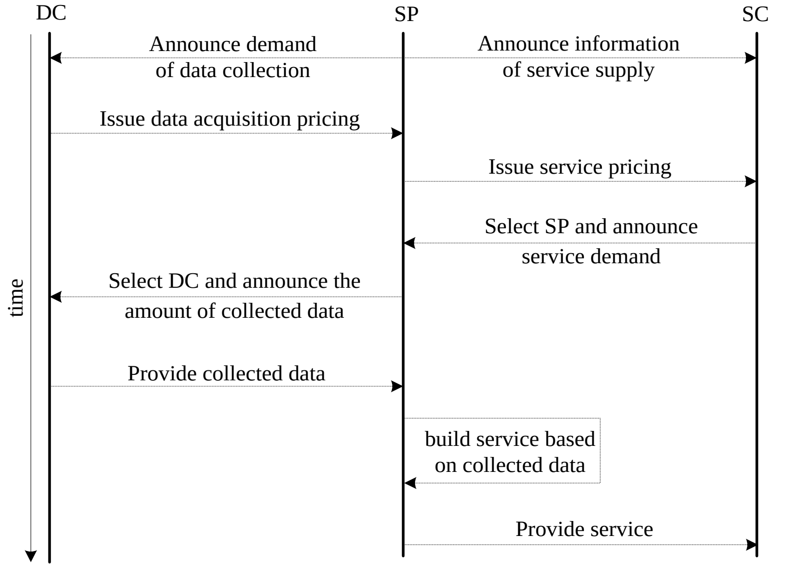

Figure 2. The interaction between the leader (SP) and followers (DC and SC)

Performance evaluation

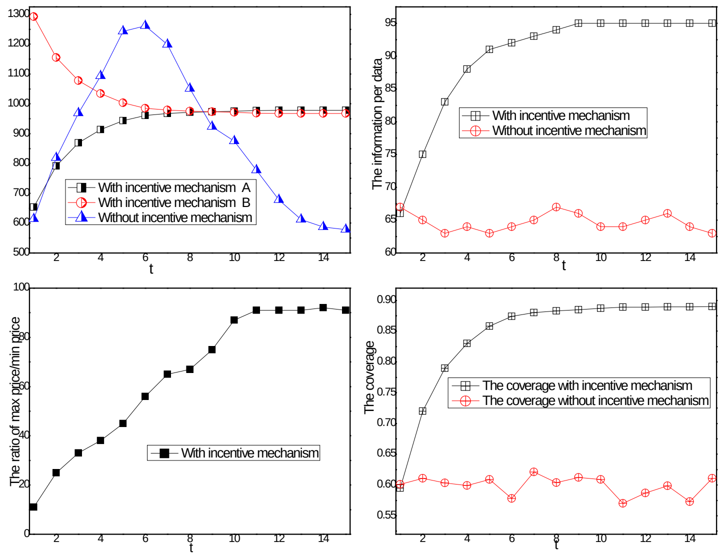

Figure 3. Performance evaluation of QUOIN

To evaluate performance of the proposed QUOIN, we compare it with performance of a direct data collection strategy. Figure 3 shows experimental results in terms of the amount of data, the amount of information, a price for collecting data, and the data coverage, respectively, over the time. The upper left of Figure 3 shows the amount of data (i.e., the number of data packets) collected by an SP. Without the incentive mechanism, it fluctuates as a price goes high and low, while with QUOIN, it always converges to an expected level steadily whether the amount of data is initialized as low or not at the beginning of the experiment (indicating as A for the low amount and B for the high amount in the upper left of Figure 3). The upper right of Figure 3 shows the amount of information contained in each data collected by the SP. Every collected data contains low quality information (e.g., the data timeliness is low) without applying QUOIN. With QUOIN, every data contains quality and usable information because low price for valueless data prevents SPs from collecting such unusable data. The lower left of Figure 3 presents a ratio of the maximum price to the minimum price for collecting data by using QUOIN. It demonstrates that QUOIN successfully makes data collection efficient and properly gives incentives to DCs. SPs sets a high price for important and scarce data in a perception area and sets a low price for redundant data, so that difference between the two prices is very big. Meanwhile, the difference is very small without using QUOIN which will lead to discourage DCs to collect “better” information. The lower right of Figure 3 shows the proportion of information covering perception areas by comparing with another data collection strategy. Obviously, the coverage using QUOIN is higher than that of the data collection strategy, which can ensure providing better services for SCs. Therefore, the experiment results show that our proposed QUOIN is efficient and effective for all participants in crowd sensing networks.

Conclusions and future work

In this article, we have investigated challenges by first identifying requirements to design effective incentive mechanisms in crowd sensing networks and then discussing whether existing techniques are sufficient for the emergence of new applications. Then, we have proposed an efficient market-based incentive mechanism called QUOIN and demonstrated that efficacy of its performance by simulation experiments. Several potential research directions on QUOIN for crowd sensing networks are outlined below. (1) Researches for game approaches based on multi-incentive mechanisms to maximize the total crowd sensing network welfare: In existing works, an SP, an SC, and a DC often use their own incentive mechanisms respectively, where although it is possible to make them to achieve a certain degree of revenue optimization, whole welfare for crowd sensing networks is not necessarily maximized. Therefore, considering joint multi-incentive mechanisms to maximize global welfare is an important research issue. (2) The credit or reputation-based incentive mechanism in crowd sensing networks: Credit or reputation is proved to be a powerful stimulus to encourage participants to be more cooperative for data collection. (3) The security and privacy-aware incentive mechanism: Near real-time information provided by participants in crowd sensing networks also gives some leakage channels for privacy issue. So, it is also challenging to keep the participants' enthusiasm to join crowd sensing activities under the premise of ensuring the privacy and security of DC.

Acknowledgment

This work was supported in part by the National Natural Science Foundation of China (61379110, 61073104, 61272149, 61272494), The National Basic Research Program of China (973 Program) (2014CB046305), JSPS KAKENHI Grant Number JP16K00117, JP15K15976, and KDDI Foundation. Anfeng Liu is the corresponding author.

References

[1] M. Dong et al., "Quality-of-Experience (QoE) in emerging mobile social networks," IEICE Trans. on Information and Systems, vol. 97, no. 10, 2014, pp. 2606-2612.

[2] X. Liu et al., "Service Pricing Decision in Cyber-Physical Systems: Insights from Game Theory." IEEE Trans. on Services Computing. vol. 9, no. 2, 2016, pp. 186-198.

[3] X. Liu et al., "An incentive game based evolutionary model for crowd sensing networks," Peer-to-Peer Networking and Applications, vol. 9, no. 4, 2016, pp.692-711.

[4] Waze "Waze - outsmarting traffic, together," http://www.waze.com/, 2013.

[5] Weather-Lah "WeatherLah iPhone application,"http://itunes.apple.com/us/app/weatherlah/id411646329?mt=8, 2012.

[6] Mana Rapid Transit "Mana Rapid Transit iPhone application," http://itunes.apple.com/sg/app/mana-rapid-transit/ id501961346?mt=8, 2012.

[7] D. Yang et al., "Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing," The 18th annual international conference on Mobile computing and networking (Mobicom '12), 2012, pp. 173-184.

[8] J. S. Lee et al., "Sell your experiences: A market mechanism based incentive for participatory sensing," 2010 IEEE International Conference on Pervasive Computing and Communications (PerCom 2010), 2010, pp. 60-68.

[9] T. Luo et al., "Profit-maximizing incentive for participatory sensing," IEEE Conference on Computer Communications (IEEE INFOCOM 2014), 2014, pp. 127-135.

[10] C. K. Tham et al., "Quality of contributed service and market equilibrium for participatory sensing," IEEE Trans. on Mobile Computing, vol. 14, no. 4, 2015, pp. 829-842.

[11] T. G. Rodrigues, et al., "Hybrid Method for Minimizing Service Delay in Edge Cloud Computing through VM Migration and Transmission Power Control," IEEE Trans. on Computers, vol. 66, no. 5, 2017, pp. 810-819.

[12] N. Kato, et al., "The Deep Learning Vision for Heterogeneous Network Traffic Control: Proposal, Challenges, and Future Perspective," IEEE Wireless Communications, vol. 24, no. 3, 2017, pp. 146-153.

[13] S. M. Yu et al., "Game-theoretic understanding of price dynamics in mobile communication services," IEEE Trans. on Wireless Communications, vol.13,no.9, 2014, pp.5120-5131.

[14] C. H. Chiu et al., "Price wall or war: The pricing strategies for retailers," IEEE Trans. on Systems, Man, and Cybernetics - Part A: Systems and Humans, vol. 39, no. 2, 2009, pp. 331-343.

[15] G. Nan, et al., "Stackelberg game for bandwidth allocation in cloud-based wireless live-streaming social networks, IEEE Systems Journal, vol. 8, no. 1, 2014, pp. 256-267.

Biographies

Kaoru Ota (ota@csse.muroran-it.ac.jp**)** received MSc degree at Oklahoma State University, US in 2008 and Ph.D degree at the University of Aizu, Japan in 2012. She is an Assistant Professor with Muroran Institute of Technology, Japan. Her research interests include wireless networks and mobile computing.

Mianxiong Dong (mx.dong@csse.muroran-it.ac.jp) received B.S., M.S. and Ph.D. in Computer Science and Engineering from the University of Aizu, Japan. He is currently with Muroran Institute of Technology, Japan. His research interests include wireless sensor networks, vehicular ad-hoc networks, wireless security.

Jinsong Gui (jsgui2010@mail.csu.edu.cn) received the MS and PhD from Central South University, China, in 2004 and 2008, respectively. He is currently an Associate Professor in the School of Information Science and Engineering, Central South University. His research interests cover the general area of distributed systems.

Anfeng Liu (afengliu@mail.csu.edu.cn) is a Professor of School of Information Science and Engineering of Central South University, China. He received the M.Sc. and Ph.D degrees from Central South University, China, 2002 and 2005, both in computer science. His major research interest are crowd sensing network and wireless sensor network.

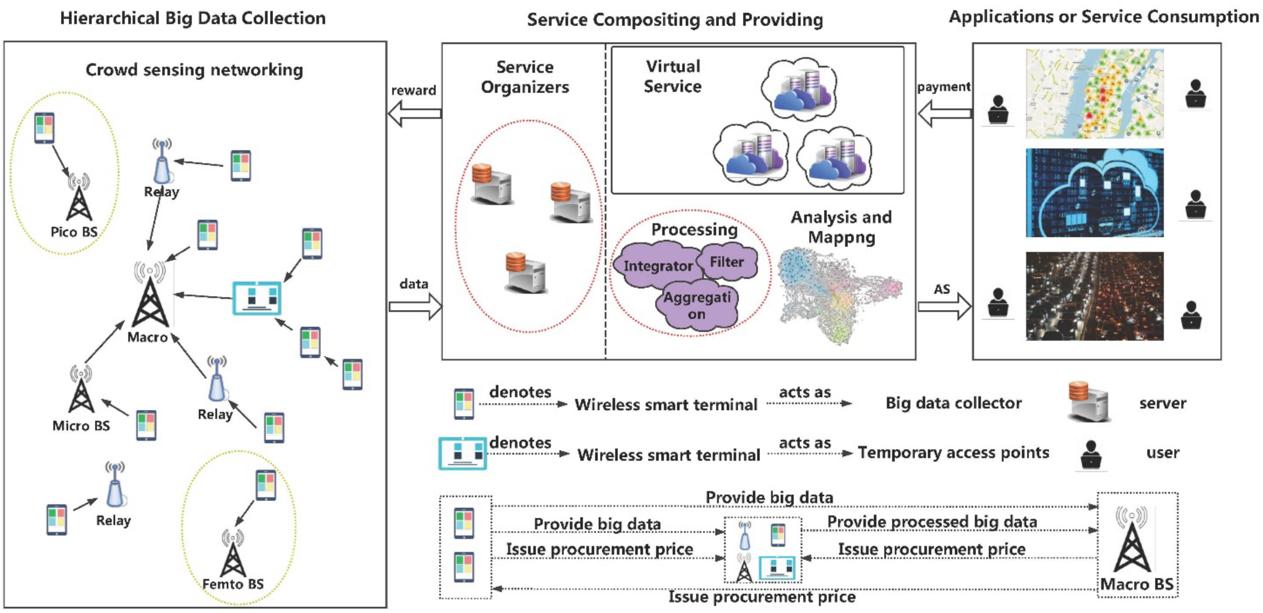

Figure 1. General architecture of big data collection in crowd sensing network

Table 1. Iterative process for the entire incentive game mechanism

Algorithm 1: The pseudo-code of QUOIN

Scenario

Set Service Provider *set* SP={SP_1, SP_2, …, SP_m};

Set Data Collector *set* DC={DC_1, DC_2, …, DC_n};

Set Service Consumer *set* SC={SC_1, SC_2, …, SC_g};

Initialization

Initialize value of profits with a data collection strategy and incentive parameter ξ for each DC

Initialize value of profits with a service consumption strategy and the initial price of services for each SC

Do while

DO **While** Any SP does not gain the maximum value of the utility function**;**

For each moment t, each SP changes the price of services during the epoch Δt;

Each SC changes its service consumption strategy for each slot $\Delta\tau$;

Each DC changes its data collection strategy for each slot $\Delta\tau$;

t = t + 1;

End For

End do

End do

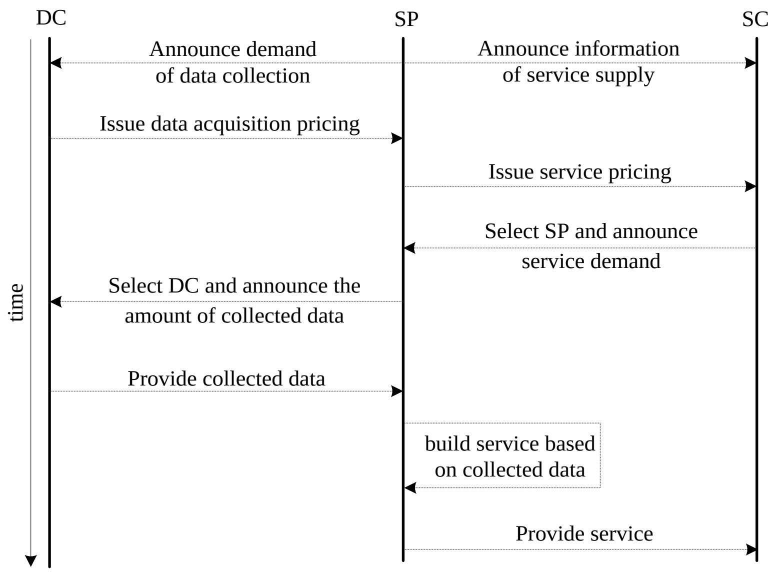

Figure 2. The interaction between the leader (SP) and followers (DC and SC)

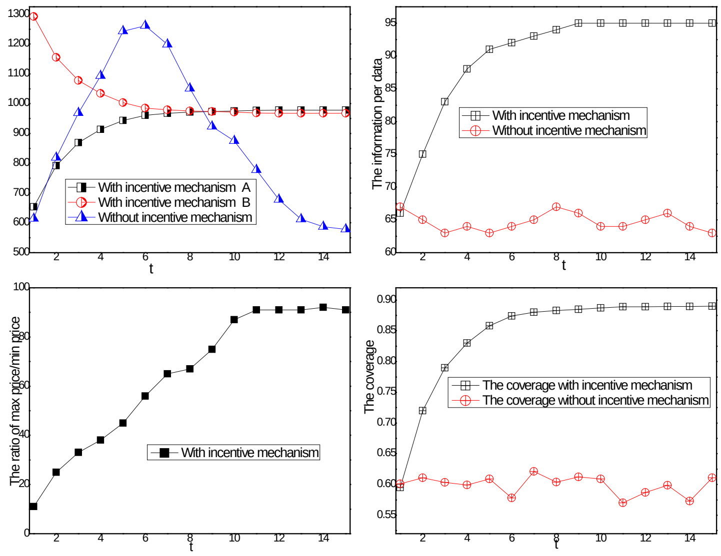

Figure 3. Performance evaluation of QUOIN