Impact of Incentive Mechanism in Participatory Sensing Environment

Niwat Thepvilojanapong*, Tomoya Tsujimori*, Hao Wang†, Yoshikatsu Ohta*, Yunlong Zhao†, and Yoshito Tobe‡
* *Department of Information Engineering, Mie University*
1577 Kurimamachiya-cho, Tsu city, Mie, Japan
E-mail: {wat, tujimori, ohta}@net.info.mie-u.ac.jp
† *School of Computer Science and Technology, Harbin Engineering University*
Nantong Street No. 145, 21#320, Harbin, Heilongjiang Province, China
E-mail: {halinw, zhaoyunlong}@hrbeu.edu.cn
‡ *Department of Integrated Information Technology, Aoyama Gakuin University*
5–10–1 Fuchinobe, Chuo-ku, Sagamihara city, Kanagawa, Japan
E-mail: yoshito-tobe@rcl-aoyama.jp

***Abstract*—Nowadays, the number of smartphone users is growing rapidly. Recent smartphones equipped with several sensors are convenient apps for collecting information in participatory sensing environment. However, contributing sensing data requires time and monetary cost, which hinder many people from participation. To realize active and efficient sensing activities, incentive mechanism is indispensable. This paper proposes *SenseUtil*, utility-based incentive for participatory sensing. SenseUtil applies the concept of micro economics, where demand and supply decide the value of sensed data. The incentive dynamically changes along the time according to several factors such as sensing frequency, nearby sensing points and users' preference. To study the impact of incentive mechanism, we conducted simulation study. The results show that people actively participate in sensing tasks while keeping additional cost fewer than three percent in comparison with non-incentive scenarios.**

***Keywords*-participatory sensing; incentive; utility functions; phone sensing; SenseUtil; simulation.**

I. Introduction

The number of smartphone users is growing rapidly [1]–[3]. It has been reported that the smartphone penetration in five leading European markets (France, Germany, Italy, Spain and the United Kingdom) is 54.6% of mobile phone users by the end of October 2012 [3]. In addition to cellular communication standards (2G/3G/4G), smartphones support several communication technologies including Wi-Fi 802.11 a/b/g/n, Bluetooth and near field communication (NFC). It also comes with high-performance processor and various kinds of sensors such as accelerometer, gyroscope, magnetometer, compass, GPS, barometer, microphone, ambient light, camera and so on. These features of current smartphones are useful for many apps which attract new users.

Recently, participatory sensing using such smartphones has been received much attention from researchers [4]. Smartphone sensing platforms, recruitment framework, energy-efficient techniques and several context-aware apps have been proposed in the literature [5]–[9]. However, many smartphone users are not likely to participate in sensing activities because it takes time and monetary cost for data communication. Therefore, incentive mechanism is indispensable to realize *active* participatory sensing by urging people to report sensed data [10], [11].

This paper proposes *SenseUtil*, a utility-based incentive framework for participatory sensing. In this model, *consumers* who need data pay reward to *producers* who carry out sensing tasks and report the data. SenseUtil applies the concept of micro economics, where demand and supply decide the value of sensed data. The demand and supply depend on many factors including location, data types and users' preference, and they also change along the time dynamically. In particular, SenseUtil determines the value of sensing activities by defining utility functions which are used to calculate *economical reward*. SenseUtil aims to maximize sensing activities while maintaining reasonable sensing cost. To study the impact of SenseUtil, we conducted simulation study. The results show that people actively participate in sensing tasks while keeping additional cost fewer than three percent in comparison with non-incentive scenarios.

This paper is organized as follows. Section II describes SenseUtil framework. Section III evaluates the benefit of SenseUtil through simulation study. Related work is discussed in Section IV, and we conclude our study in Section V.

II. SenseUtil Framework

SenseUtil consists of three main players: consumers, producers and a server. A *consumer* would like to have data being sensed at a remote area, while a *producer* is willing to carry out such sensing tasks. A person can serve as both the consumer and producer. A central *server* is responsible to manage interactions between consumers and producers. Interactions of three players are summarized in Figure 1 and the details of SenseUtil are described in this section.

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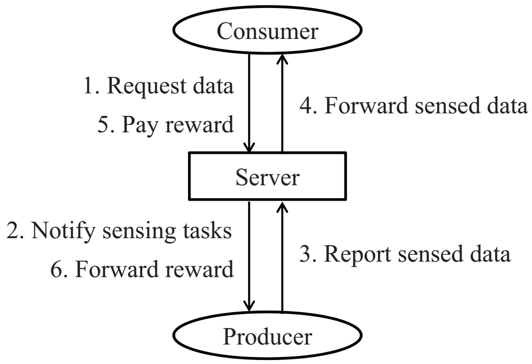

Figure 1. Interactions of a consumer, a server and a producer.

Table I
NOTATIONS.

D_{th}^k	Distance threshold of a producer k
U_{th}^k	Utility threshold of a producer k
T_{th}^k	Elapsed time threshold of a producer k
U	Independent utility
U_{min}	Minimum utility
U_{max}	Maximum utility
V	Correlated utility
P_i	A point of interest (POI) i
t	Current time
t_i	Latest sensing time at P_i
a, α, b	Constants
w_{ij}	Weight for calculating correlated utility
d_{ij}	Distance between P_i and P_j

A. Consumers

A Consumer defines a *Point of Interest (POI)* where data should be sensed. In addition to location information, POI also includes starting time, expiry time and data type (i.e., which kind of data need to be sensed). The consumer sends POI information to the server on demand. When receiving corresponding data, the consumer pays reward determined by the utility functions (see Section II-D).

B. A Server

A server is a middleman between consumers and producers (Figure 1). It maintains POIs' information or the sensing tasks requested by consumers and updates corresponding reward of each POI periodically or on demand. The producers acquire detailed information of sensing tasks by exploiting pull and/or push services.

By adopting the *pull* or *on-demand services*, the server dispatches POI information upon receiving a request from a consumer. The producers may use the pull service to avoid being overwhelmed by too frequent update of POI information. In addition, the producers can use the pull service to update current reward of POI. On the other hand, the *push service* provides two methods for dispatching the information to producers, i.e., instant and periodic push. The *instant push* allows the server to dispatch the POI information immediately upon receiving new POI information from a consumer. The service is beneficial for producers who would like to have the information of new POI in real-time manner; thus, they can act fast to receive rewards. The producers subscribe to *periodic push* will receive the POI information periodically.

The server is also responsible to collect sensing data from producers and forward the data to consumers. In addition, the process of collecting payment and rewarding are handled by the server.

C. Producers

As described above, a producer receives the information of sensing tasks including current reward from the server through pull and/or push services. The producer can also determines her preferences including area of interest (e.g., a limited area based on current position or any specific area), maximum number of tasks, minimum reward, frequency of push-based notification, and so on.

The behavior of a producer depends on current position and reward of sensing task. A producer k will carry out a sensing task if all the following conditions satisfy: (1) her position is not far from a POI, i.e., the distance between the producer and the POI is shorter than or equal to D_{th}^k, (2) the reward is higher than a threshold U_{th}^k, and (3) the time elapsed from previous sensing at the same POI is longer than T_{th}^k. The underlying reason of the third condition is to avoid too frequent sensing at the same POI.

If the above conditions satisfy, the producer changes the route by moving towards the POI, carries out the sensing task and moves towards the original destination. By default, the producer uses the maximum speed in order to minimize moving time. However, the producer may move with the current speed if she is not in a hurry. After the task has been done, the producer receives reward via the server.

Note that the producers may calculate utility by using (1) or (2) introduced in Sect. II-D. However, the producers may have incorrect value of utility because they do not know when other producers carry out the sensing tasks. The producers need to use the pull service to ask for current utility maintained by the server.

D. Utility Functions

This section introduces utility functions which are used to calculate the value of sensing data POI i (i.e., P_i) at a given time t. The consumers have to pay reward according to the utility functions. We consider two cases when calculating utility, that is, independent and correlated POIs. Table I summarizes notations used in the paper.

Independent POI means sensing data of P_i are independent of other POIs. Basically, the utility is initialized to the minimum value (U_{min}) and increases along the time until reaching the maximum value (U_{max}). Equation (1) defines the utility of POI i at time t.

$$U(P_i, t) = \max\left(U_{min}, \min\left(U_{max}, a(t - t_i)\right)\right), \quad (1)$$

where t_i is the latest sensing time at P_i and is initialized to the starting time of P_i. While sensing task is not done, the utility increases along the time due to higher demand of consumers. A coefficient a ($a > 0$), which is determined by the consumer, determines how fast the utility increases. The consumer also decides U_{min} and U_{max} because the value of data sensed at each POI may be unequal.

When a sensing task has been done, the utility is reset to the minimum value and starts to increase again. The underlying reason of (1) is straightforward. Consumers would like to urge producers to carry out sensing tasks but they would like to avoid too frequent sensing which is not likely to give meaningful information for most of applications. Because some kinds of sensing data do not change abruptly, it would be better to have an interval between each sensing. By applying the above equation, consumers pay less for each sensing if sensing interval is short while they pay more if the interval is long.

Next, we consider *correlated POI*, $V(P_i, t)$, where the utility of P_i correlates to nearby j POIs ((2)).

$$V(P_i, t) = \begin{cases} \alpha U(P_i, t) + \\ \quad (1-\alpha)\frac{\sum_{\forall j} w_{ij} U(P_j, t)}{\sum_{\forall j} w_{ij}} & \text{if } P_j \neq \varnothing, \\ U(P_i, t) & \text{if } P_j = \varnothing. \end{cases} \quad (2)$$

Equation (2) includes the utilities of nearby j POIs, i.e., $U(P_j, t)$ which is calculated by (1) and weighted by w_{ij}. The weight w_{ij} is inversely proportional to the distance d_{ij} between P_i and P_j. In particular, $w_{ij} = \frac{b}{d_{ij}}$, where b ($b > 0$) is a constant. In addition, a constant α ($0 \leq \alpha \leq 1$) is a ratio to determine the weight of P_i and all nearby POIs' utility. If nearby POI does not exist, we use (1), i.e., if $P_j = \varnothing$, $\alpha = 1$.

The nearby j POIs to be considered in (2) are determined by the area centered at P_i and/or the number of nearest POIs centered at P_i. It is explicit from (2) that if the utilities of nearby POIs are high, $V(P_i, t)$ will be high because P_i and nearby j POIs are not sensed for a while. If any nearby j POIs has been sensed recently, $V(P_i, t)$ will be low because nearby POIs are likely to give similar sensing data.

E. Economical Point System

Any kinds of currency including monetary currency, virtual currency and a point system can be applied to SenseUtil for payments and rewards. Point system is widely adopted by real-world stores and electronic commerce for long time and has been proved to be a successful strategy to urge purchasing and maintain loyalty of customers.

III. Performance Evaluation

We conducted simulations to study the impact of incentive mechanism. The simulation program is written in Java language.

Table II
SIMULATION PARAMETERS.

Simulation area (m^2)	500×500
Sensing area	%80 of simulation area
Number of POIs	10
Number of producers	10
Minimum speed (m/s^2)	3
Maximum speed (m/s^2)	7
Maximum pause time (s)	9
Simulation duration (s)	1,000
D^k_{th} (m)	24
U^k_{th}	13
T^k_{th} (s)	10
U_{min}	10
U_{max}	50
a	1
α	0.5
b	1

A. Simulation Setup

Mobile users or producers move according to the random waypoint model [12]. Each mobile user is initially placed at a random position within the simulation area. As the simulation progresses, each mobile user pauses at its current location for a random period, which we call the pause time, and then randomly chooses a new location to move to and a velocity between the minimum and maximum speeds at which to move there. The pause time is randomly chosen between zero and maximum pause time. Each mobile user continues this behavior, alternately pausing and moving to a new location, for the duration of the simulation.

Consumers pick random POIs within a *sensing area* which is defined as a percentage of the entire simulation area. The center and aspect ratio of both sensing and simulation areas are the same, i.e., the sensing area is a subset of the simulation area. All POIs last from the beginning until the end of simulations.

The parameters of simulation including those of the random waypoint model and utility functions are summarized in Table II. We run simulation 10 times with different patterns of node movement.

B. Simulation Scenarios

We consider the following scenarios in our simulation.

- **Non-incentive scenario.** Since incentive is not available in this scenario, each node moves according to the mobility model and carry out sensing tasks if they happen to pass through a POI. Based on preliminary experiments, nodes rarely pass through POIs. Thus a sensing task is supposed to be done if a node stays within five meters from a POI in our evaluation (Section III-D).
- **Incentive-aware scenario.** Both of utility models ((1) and (2)) are adopted in this scenario. The nearby j POIs are determined by the circle centered at P_i with the radius of 50 meters. The server uses the push-based

service to announce POIs and corresponding rewards at the beginning of the simulations. When the distance between a producer and a POI is shorter than or equal to the threshold D_{th}^{k}, the producer queries the server about current reward by using the pull service.

C. Evaluation Metrics

The following metrics are useful to study the impact of incentive.

- **Number of sensings.** We count the number of sensing tasks done by all producers in a simulation. The number of sensings is a straightforward metric to evaluate the benefit of incentive. Higher number of sensings means more people help collect sensing data.
- **Paid reward per sensing.** We calculate average reward per sensing in each simulation. Then the percentage of decreased reward when applying incentive is calculated as follows.

$$\%\text{Decrease} = \frac{U_{none} - U_{incentive}}{U_{none}} \times 100, \quad (3)$$

where U_{none} and $U_{incentive}$ are average reward per sensing in non-incentive and incentive-aware scenarios, respectively. Note that, we assume incentive is available in non-incentive scenarios for comparison purpose. In particular, we use the same utility models ((1) and (2)) to calculate rewards when nodes are supposed to do sensing tasks. The incentive does not actually exist and nodes move according to the mobility model.
- **Traveled distance.** There is cost to do sensing tasks because producers have to change their routes and take additional time to visit POIs. Thus we compare traveled distance between non-incentive and incentive-aware scenarios. We calculate the percentage of increased distance when applying incentive as follows.

$$\%\text{Increase} = \frac{D_{incentive} - D_{none}}{D_{none}} \times 100, \quad (4)$$

where $D_{incentive}$ and D_{none} are average traveled distance per node in incentive-aware and non-incentive scenarios, respectively.

D. Simulation Results

The average results of 10 runs are summarized in Table III which shows both absolute results and relative results in percentage. The detailed results of each run for all three metrics are shown in Figures 2 (the number of sensings), 3 (average reward per sensing) and 4 (traveled distance per node).

The results in Table III show that the number of sensings increases 391% and 375% when adopting independent and correlated incentives, respectively. Figure 2 shows the results of each individual run. As one would expect, incentive urges more people to carry out sensing tasks.

Table III
SIMULATION RESULTS OF 10 RUNS.

	Non-incentive	U	V
Total number of sensings	24.9	122.2	118.3
Increased number of sensings (%)	N/A	391%	375%
Average reward per sensing	46.0	37.6	36.6
Decreased reward per sensing (%)	N/A	18%	21%
Average distance per node (m)	4,638	4,744	4,745
Increased distance per node (%)	N/A	2.28%	2.31%

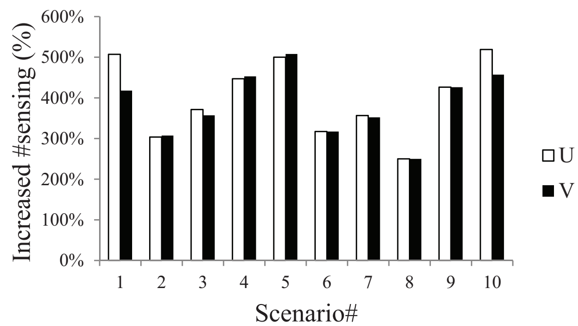

Figure 2. Percentage of increased number of sensing.

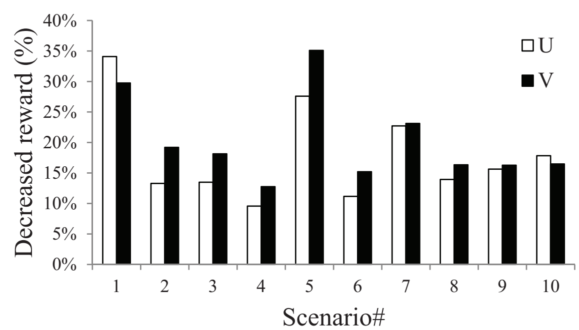

Figure 3. Percentage of decreased reward.

Next we consider the percentages of decreased reward when applying incentives (Figure 3). The paid rewards per sensing decrease 18% and 22% in average when applying independent and correlated incentives, respectively (Table III). The rewards decrease because sensing tasks are done more frequent. We note here that the reward is reset to the minimum value when a sensing task has been done. In other words, it means sensing interval is shorter and sensing data of each POI are updated more frequent. This is a benefit for consumers who pay attention on the freshness of data. In addition, the consumers pay less for each sensing task. When comparing two utility models, the rewards of the correlated model (V) are slightly lower than those of the independent model (U) because the weighted factor α of V is set to 0.5. As a result, the rewards of the correlated model increase slower than the independent model.

The last metric we consider is the percentages of increased distance when applying incentive (Figure 4). The impact of both independent and correlated models is similar in which

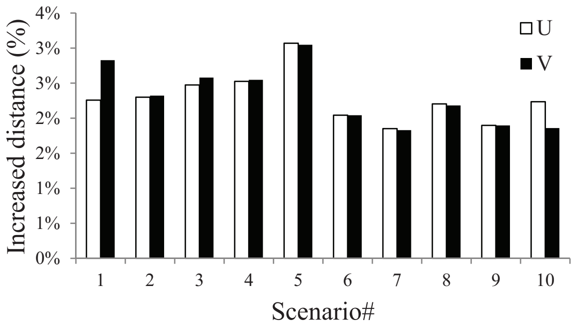

Figure 4. Percentage of increased distance.

the traveled distance increases merely two percent. We can infer from the results that the producers do not need to move much farther than their originally planned routes. In other words, it takes a moment to visit POIs before moving towards the original destinations.

We conclude that incentive is a good motivation to increase sensing frequency. Producers get rewards for their jobs, while consumers pay less for each sensing task in comparison with non-incentive scenarios. Additional cost in terms of traveled distance is also very low.

IV. Related Work

Participatory sensing using mobile phones is an active and growing research area with a number of open issues and challenges [4]. The Internet of Things (IoT), several smartphone sensing platforms, information dissemination algorithms, energy-efficient techniques and context-aware apps, which are the complement of SenseUtil framework, have been proposed in the literature [5]–[9], [13]–[15]. Guo et al. present hybrid social networking, which highlights the interweaving and cooperation of heterogeneous communities [13]. Guo et al. extract the embedded intelligence about individual, environment, and society by exploring the various interactions between humans and the IoT [14]. Askus [15] is a mobile social platform which allows users to send a request to a group of potential people in a remote area to do a task. Similar to Askus, other existing sensing platforms are voluntary systems, i.e., sensing data are contribution from cooperative users. SenseUtil can be applied directly to such previous works.

To realize active and efficient sensing activities, incentive mechanism has been introduced recently. Most of previous works adopt auction algorithms to decide the value of sensing data [10], [11], [16], [17]. Unlike previous works, SenseUtil's consumers indirectly determine their bids through some factors such as minimum price, maximum price, changing rate of price. In addition, the bid price of SenseUtil dynamically changes according to nearby POIs and sensing frequency without any further intervention of consumers.

V. Conclusion

To urge people participate in sensing activities, we have proposed SenseUtil, a utility-based incentive mechanism for mobile phone sensing. SenseUtil introduces utility functions which are used to determine the value of sensing data. When producers finish sensing tasks, they get rewards from consumers according to the utility functions. A salient feature of SenseUtil is dynamic incentive which changes along the time depending on sensing activities of all participants. In comparison with non-incentive environment, the simulation study shows that more people participate in sensing tasks while additional traveled distance of participants is less than three percent.

One of future works is to study the benefit of incentive mechanism by adopting other mobility models. We also plan to include other factors in the proposed utility models and evaluate their impact. Another interesting issue is to let each producer use different conditions to determine whether to do a sensing task.

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