User-Centric Participatory Sensing: A Game Theoretic Analysis
Xiaoyan Mo, Zhang Li, Lin Gao, Bin Cao, Tingting Zhang, and Tong Wang

Abstract—Participatory sensing (PS) is a novel and promising sensing network paradigm for achieving a flexible and scalable sensing coverage with a low deploying cost, by encouraging mobile users to participate and contribute their smartphones as sensors. In this work, we consider a general PS system model with location-dependent and time-sensitive tasks, which generalizes the existing models in the literature. We focus on the task scheduling in the user-centric PS system, where each participating user will make his individual task scheduling decision (including both the task selection and the task execution order) distributively. Specifically, we formulate the interaction of users as a strategic game called Task Scheduling Game (TSG) and perform a comprehensive game-theoretic analysis. First, we prove that the proposed TSG game is a potential game, which guarantees the existence of Nash equilibrium (NE). Then, we analyze the efficiency loss and the fairness index at the NE. Our analysis shows the efficiency at NE may increase or decrease with the number of users, depending on the level of competition. This implies that it is not always better to employ more users in the user-centric PS system, which is important for the system designer to determine the optimal number of users to be employed in a practical system.

I. INTRODUCTION

A. Background and Motivations

With the development and proliferation of smartphones with rich build-in sensors and advanced computational capabilities, we are witnessing a new sensing network paradigm known as participatory sensing (PS) or mobile crowd sensing (MCS) [1]–[3], which relies on the active participation and contribution of smartphone users (to contribute their smartphones as sensors). Comparing with the traditional approach of deploying sensor nodes and sensor networks, this new sensing scheme can achieve a higher sensing coverage with a lower deployment cost, and hence it better adapts to the changing requirement of tasks and the varying environment. Therefore, it has found a wide range of applications in environment, infrastructure, and community monitoring [4]–[7].

A typical PS framework often consists of (i) a service platform (server) residing in the cloud and (ii) a set of participating smartphone users distributed and travelling on the ground [1]–[3]. The service platform launches many sensing tasks, possibly initiated by different requesters with different data requirements for different purposes; and users subscribe to one or multiple task(s) and contribute their sensing data. Due to the location-awareness and time-sensitivity of tasks and the geographical distribution of users, a proper scheduling of tasks among users is critical for a PS system. For example, if a task is scheduled to a user far away from its target location, the user may not be able to travel to the target location in time so as to complete the task successfully.

Depending on who (i.e., the server or each user) will make the task scheduling decision, there are two types of different PS models: Server-centric Participatory Sensing (SPS) [8]–[13] and User-centric Participatory Sensing (UPS) [14]–[18]. In the SPS model, the server will make the task scheduling decision and determine the joint scheduling of all tasks among all users, often in a centralized manner with complete information (as in [8]–[13]). In the UPS model, each participating user will make his individual task scheduling decision and determine the tasks he is going to execute, often in a distributed manner with local information (as in [14]–[18]). Clearly, the SPS model assigns more control to the server to make the (centralized) joint scheduling decision, hence can better satisfy the requirements of various tasks. The UPS model, however, distributes the control among the participating users and enables each user to make the (distributed) individual scheduling decision. Hence, it can faster adapt to the varying environment and the changing requirement of individual users.

In this work, we focus on the task scheduling in the UPS model, where the task scheduling decision is made by each user distributively. Comparing with SPS, the UPS model has the appealing features of (i) low communication overhead and (ii) low computational complexity, by distributing the complicated central control (and computation) among numerous participating users, hence it is more scalable. Therefore, UPS is particularly suitable for a fast changing environment (where the information exchange in SPS may become a heavy burden) and a large-scale system (where the centralized task scheduling in SPS may be too complicated to compute in real-time), and hence it has been adopted in some commercial PS systems, such as Field Agent [19] and Gigwalk [20].

B. Related Work

Many existing works have studied the task scheduling problem in different UPS models, aiming at either minimizing the energy consumption (e.g., [14]–[16]) or maximizing the social surplus (e.g., [17], [18]). Specifically, in [14], Jiang et al. studied the peer-to-peer based data sharing among users in mobile crowdsensing, but they considered neither the location-dependence nor the time-sensitivity of tasks. In [15], Sheng et al. studied the opportunistic energy-efficient collaborative sensing for location-dependent road information. In [16], Zhao...
et al. studied the fair and energy-efficient task scheduling in mobile crowdsensing with location-dependent tasks. In [17], He et al. studied the social surplus maximization for location-dependent task scheduling in mobile crowdsensing. However, the above works did not consider the time-sensitivity of tasks, where each task can be executed at any time. In this work, we will consider both the location-dependence and the time-sensitivity of tasks.

Cheung et al. in [18] studied the social surplus maximization scheduling for both location-dependent and time-sensitive tasks, where each task must be executed at a particular time. Inspired by [18], in this work, we will consider a more general task model, where each task can be executed within a valid time period (instead of the particular time in [18]). Clearly, our task model generalizes the existing models in [14]–[18], as it will degenerate to the models in [14]–[17] by simply choosing an infinitely large valid time period for each task, and degenerate to the model in [18] by simply shrinking the valid time period of each task to a single point.

C. Solution and Contributions

In this work, we consider a general UPS model consisting of multiple tasks and multiple smartphone users, where each user will make his individual task scheduling decision distributively (e.g., deciding the set of tasks he is going to execute). Tasks are (i) location-dependent, each associated with one or multiple target location(s) at which the task will be executed, and (ii) time-sensitive, each associated with a valid time period within which the task must be executed.

Moreover, users are geographically dispersed (i.e., each associated with an initial location) and can travel to different locations for executing different tasks. As different tasks may have different valid time periods, each user needs to decide not only the task selection (i.e., the set of tasks he is going to execute) but also the execution order of the selected tasks. This is also the key difference between the task scheduling in our work and that in [18], which focused on the task selection only, without considering the execution order.\(^1\) Note that our task scheduling problem (i.e., task selection and order optimization) is much more challenging than that in [18] (i.e., task selection only), as even if the task selection is given, the execution order optimization is still an NP-hard problem.

Figure 1 illustrates an example of such a task scheduling decision in a UPS model with location-dependent time-sensitive tasks. Each route denotes the task scheduling decision (i.e., task selection and execution order) of each user. For example, user 1 chooses to execute tasks \{1, 2, 3, 4\} in order, user 2 chooses to execute tasks \{5, 1, 6\} in order, and user 3 chooses to execute tasks \{7, 8, 9\} in order.

Game Formulation: When a user executes a task successfully (i.e., at the target location and within the valid time period of the task), the user will obtain a certain reward provided by the task owner. When multiple users execute the same task, they will share the reward equally as in [18]. This makes the task scheduling decisions of different users coupled with each other, leading to a strategic game situation.

We formulate such a game, called Task Scheduling Game (TSG), and perform a comprehensive game-theoretic analysis.\(^2\) Specifically, we first prove that the TSG game is a potential game [21], which guarantees the existence of Nash equilibrium (NE). Then we analyze the social efficiency loss at the NE (comparing with the socially optimal solution) induced by the selfish behaviors of users. We further show how the efficiency loss changes with the user number and user type.

In summary, the main results and key contributions of this work are summarized as follows.

- General Model: We consider a general UPS model with location-dependent time-sensitive tasks, which generalizes the existing task models in the literature.
- Game-Theoretic Analysis: We perform a comprehensive game-theoretic analysis for the task scheduling in the proposed UPS model, by using a potential game.
- Performance Evaluation: We evaluate the efficiency loss and the fairness index at the NE under different situations. Our simulations in practical scenarios with different types of users (walking, bike, and driving users) show that the efficiency loss can be up to 70% due to the selfish behaviors of users.
- Observations and Insights: Our analysis shows that the NE performance may increase or decrease with the number of users, depending on the level of competition. This implies that it is not always better to employ more users in the UPS system, which can provide a guidance for the system designer to determine the optimal number of users to be employed in a practical system.

The rest of the paper is organized as follows. In Section II, we present the system model. In Section III and IV, we formulate the task scheduling game and analyze the Nash equilibrium. We present the simulation results in Section V, and finally conclude in Section VI.

\(^1\)In [18], each task is associated with a particular time, hence the execution order is inherently given as long as the tasks are selected.

\(^2\)Game theory has been widely used in wireless networks (e.g., [22]–[27]) for modeling and analyzing the competitive and cooperative interactions among different network entities.
II. SYSTEM MODEL

We consider a user-centric UPS system consisting of a sensing platform and a set \( \mathcal{N} = \{1, \cdots, N\} \) of mobile smartphone users. The platform announces a set \( \mathcal{S} = \{1, \cdots, S\} \) of sensing tasks. Each task can represent a specific sensing event at a particular time and location, or a set of periodic sensing events within a certain time period, or a set of sensing events at multiple locations. Each task \( k \in \mathcal{S} \) is associated with a reward \( V_k \), denoting the money to be paid to the users who execute the task successfully. Each user can choose the set of tasks he is going to execute. When multiple users execute the same task, they will share the reward equally as in [18]. This makes the task scheduling decisions of different users coupled with each other, resulting in a strategic game situation.

A. Task Model

We consider a general task model, where tasks are (i) location-dependent: each task \( k \in \mathcal{S} \) is associated with a target location \( L_k \) at which the task will be executed;\(^3\) and (ii) time-sensitive: each task \( k \in \mathcal{S} \) is associated with a valid time period \( T_{k1} \leq T_{k2} \) within which the task must be executed. Examples of such tasks includes the measurement of traffic events within a certain time period, or a set of sensing events at multiple locations. Each task \( k \in \mathcal{S} \) is associated with a valid time period \( T_k \), which may have a high speed and cost. Let \( C_i \) and \( R_i \) denote the travelling cost (per unit of travelling distance) and speed (m/s) of user \( i \in \mathcal{N} \), respectively.

C. Problem Description

As different tasks may have different valid time periods, each user needs to consider not only the task selection (i.e., the set of tasks to be executed) but also the execution order of the selected tasks. As shown in Figure 1, the task execution order is important, as it affects not only the user’s travelling cost but also whether the selected tasks can be executed within their valid time periods. For example, if user 1 executes task 4 first (within the time period [13:00, 14:00], say 13:30), he cannot execute tasks \{1, 2, 3\} any more within their valid time periods (all of which are earlier than 13:30). This is also one of the key differences between our problem and that in [18], which only focused on the task selection, without considering the task execution order.

III. GAME FORMULATION

As mentioned before, when multiple users choose to execute the same task, they will share the task reward equally. This makes the decisions of different users coupled with each other, leading to a strategic game situation. In this section, we will provide the formal definition for such a game.

A. Strategy and Feasibility

As discussed in Section II, the strategy of each user \( i \in \mathcal{N} \) is to choose a set of available tasks (to execute) and the execution order of the selected tasks, aiming at maximizing his payoff. Such a strategy of user \( i \) can be formally characterized by an ordered task set, denoted by

\[
s_i \triangleq \{k_1^i, \cdots, k_{|s_i|}^i\} \subseteq \mathcal{S}_i
\]

(1)

where the \( j \)-th element \( k_j^i \) denotes the \( j \)-th task selected and executed by user \( i \).

A strategy \( s_i = \{k_1^i, \cdots, k_{|s_i|}^i\} \) of user \( i \) is feasible, only if the time-sensitivity constraints of all selected tasks in \( s_i \) are satisfied, or equivalently, there exists a reasonable execution time vector such that all selected tasks in \( s_i \) can be executed within their valid time periods. Let \( T_{k1}^i, \cdots, T_{k_{|s_i|}^i}^i \) denote a potential execution time vector of user \( i \), where \( T_{k_j}^i \) denotes the execution time for the \( j \)-th task \( k_j^i \). Then, \( T_{k1}^i, \cdots, T_{k_{|s_i|}^i}^i \) is feasible, only if (i) it satisfies the time-sensitivity constraints of all selected tasks, i.e.,

\[
T_{k1}^i \leq T_{k_j}^i \leq T_{k_{|s_i|}^i}^i, \quad j = 1, \cdots, |s_i|,
\]

(2)

and meanwhile (ii) it is reasonable in the temporal logic, i.e.,

\[
\begin{cases}
T_1^i \geq \frac{D(i,k_1^i)}{R_i}, \\
T_j^i \geq T_{j-1}^i + T_{k_{j-1}^i} + \frac{D(i,k_j^i)}{R_i}, \quad j = 2, \cdots, |s_i|,
\end{cases}
\]

(3)
where \( D(i, k_i^1) = |L_i - L_{k_i^1}| \) denotes the distance between user \( i \)'s initial location \( L_i \) and the first task \( k_i^1 \), \( D(k_i^1-1, k_i^1) = |L_{k_i^1-1} - L_{k_i^1}| \) denotes the distance between tasks \( k_i^1-1 \) and \( k_i^1 \), and \( T_{i, k_i^1-1} \) denotes the time for executing task \( k_i^1-1 \).

Moreover, a strategy \( s_i \) of user \( i \) is feasible, only if it satisfies the resource budget constraint. That is,

\[
\sum_{k \in s_i} C_i,k \leq C_i.
\]  

(4)

Based on the above, we express in the following lemma the feasibility conditions for the user strategy \( s_i \).

**Lemma 1 (Feasibility).** A strategy \( s_i \) of user \( i \) is feasible, if and only if the conditions (2)-(4) are satisfied.

Intuitively, if one of the conditions in (2)-(4) is not satisfied, then the strategy \( s_i \) is not feasible as explained early. Thus, if \( s_i \) is feasible, the conditions (2)-(4) must be satisfied. One the other hand, if (2)-(4) are satisfied, the strategy \( s_i \) can be implemented successfully, hence is feasible. Due to space limit, we put the detailed proof in online technical report [28].

**B. Payoff Definition**

Given a feasible strategy profile \( s \triangleq (s_1, \ldots, s_N) \), i.e., the feasible strategies of all users, we can compute the number of users executing task \( k \in S \), denoted by \( M_k(s) \), that is,

\[
M_k(s) = \sum_{i \in N} 1_{(k \in s_i)}, \quad \forall k \in S,
\]  

(5)

where the indicator \( 1_{(k \in s_i)} = 1 \) if \( k \in s_i \), and 0 otherwise. Then, the total reward of each user \( i \) in \( N \) can be computed by

\[
r_i(s) \triangleq r_i(s_i, s_{-i}) = \sum_{k \in s_i} \frac{V_k}{M_k(s)},
\]  

(6)

which depends on both his own strategy \( s_i \) and the strategies of other users, i.e., \( s_{-i} \triangleq (s_1, \ldots, s_{i-1}, s_{i+1}, \ldots, s_N) \). The total execution cost of user \( i \) in \( N \) can be computed by

\[
c_i^{EX}(s_i) = \sum_{k \in s_i} C_i,k,
\]  

(7)

which depends only on his own strategy \( s_i \). The total travelling cost of user \( i \) in \( N \) can be computed by

\[
c_i^{TR}(s_i) = \sum_{j=1}^{\left| s_i \right|} D(k_j^{i-1}, k_j^i) \cdot C_i,
\]  

(8)

which depends only on his own strategy \( s_i \). Here we use the index \( k_j^0 \) to denote user \( i \)'s initial location. Based on the above, the payoff of each user \( i \in N \) can be written as follows:

\[
u_i(s) \triangleq u_i(s_i, s_{-i}) = r_i(s) - c_i^{EX}(s_i) - c_i^{TR}(s_i) = \sum_{k \in s_i} \frac{V_k}{M_k(s)} - c_i^{EX}(s_i) - c_i^{TR}(s_i).
\]  

(9)

Next we analyze the NE of the Task Scheduling Game.

**C. Task Scheduling Game – TSG**

Now we define the Task Scheduling Game (TSG) and the associated Nash equilibrium (NE) formally.

**Definition 1 (Task Scheduling Game – TSG).** The Task Selection Game \( T \triangleq (N, \{S_i\}_{i \in N}, \{u_i\}_{i \in N}) \) is defined by:

- **Player:** the set of participating users \( N = \{1, \ldots, N\} \);
- **Strategy:** an ordered set of available tasks \( s_i \subseteq S_i \) for each participating user \( i \in N \);
- **Payoff:** a payoff function \( u_i(s_i, s_{-i}) \) defined in (9) for each participating user \( i \in N \).

A feasible strategy profile \( s^* \triangleq (s_1^*, \ldots, s_N^*) \) is an NE of the Task Scheduling Game \( T \), if

\[
s_i^* = \arg \max_{s_i \subseteq S_i} u_i(s_i, s_{-i})
\]  

\[
s.t. s_i \text{ satisfies (2)-(4)},
\]  

(10)

for every user \( i \in N \).

**IV. GAME EQUILIBRIUM ANALYSIS**

We now analyze the NE of the Task Scheduling Game.

**A. Potential Game**

We first show that the Task Scheduling Game \( T \) is a potential game [21]. A game is called an (exact) potential game, if there exists an (exact) potential function, such that for any user, when changing his strategy, the change of his payoff is equivalent to that of the potential function. Formally,

**Definition 2 (Potential Game [21]).** A game \( G = (N, \{S_i\}_{i \in N}, \{u_i\}_{i \in N}) \) is called a potential game, if it admits a potential function \( \Phi(s) \) such that for every player \( i \in N \) and any two strategies \( s_i, s_i' \subseteq S_i \) of player \( i \),

\[
u_i(s_i, s_{-i}) - u_i(s_i', s_{-i}) = \Phi(s_i, s_{-i}) - \Phi(s_i', s_{-i}),
\]  

(11)

under any strategy profile \( s_{-i} \) of players other than \( i \).

**Lemma 2.** The Task Scheduling Game \( T \) is a potential game, with the following potential function \( \Phi(s) \):

\[
\Phi(s) = \sum_{k \in S} \sum_{m=1}^{M_k(s)} \frac{V_k}{m} - \sum_{i \in N} c_i^{EX}(s_i) - \sum_{i \in N} c_i^{TR}(s_i),
\]  

(12)

where \( M_k(s) \) is defined in (5), i.e., the total number of users executing task \( k \) under the strategy profile \( s \).

The above lemma can be proved by showing that the condition (11) holds under the following two situations: (i) a user changes the execution order, but not the task selection; and (ii) a user changes the task selection by adding an additional task or removing an existing task. Due to space limit, we leave the detailed proof in online technical report [28].

**B. Nash Equilibrium – NE**

We now analyze the NE of the proposed game. As shown in [21], an appealing property of a potential game is that it always admits an NE. In addition, any strategy profile \( s^* \) that maximizes the potential function \( \Phi(s) \) is an NE. Formally,
Lemma 3. The Task Scheduling Game $\mathcal{T}$ has at least one NE $s^* \triangleq (s_1^*, \ldots, s_N^*)$, which is given by

$$s^* \triangleq \arg \max_s \Phi(s)$$

s.t. $s_i$ satisfies (2)-(4), $\forall i \in \mathcal{N}$,

where $\Phi(s)$ is the potential function defined in (12).

This lemma can be easily proved by observing that $u_i(s_i^*, s_i^{-i}) - u_i(s_i', s_i^{-i}) = \Phi(s_i^*, s_i^{-i}) - \Phi(s_i', s_i^{-i}) \geq 0$, for any user $i \in \mathcal{N}$ and $s_i' \subseteq S_i$. The last inequality follows because $(s_i^*, s_i^{-i})$ is the maximizer of $\Phi(s)$ by (13).

C. Efficiency of NE

Now we show that the NE of the Task Scheduling Game $\mathcal{T}$, especially the one given by (13), is often not efficient.

Specifically, a strategy profile $s^o$ is socially efficient (SE), if it maximizes the following social welfare:

$$W(s) = \sum_{k \in S} V_k \cdot (1_{M_k(s) \geq 1} - \sum_{i \in \mathcal{N}} (c_{ik}^E(s_i) + c_{ik}^T(s_i)))$$

(14)

where $1_{M_k(s) \geq 1} = 1$ if $M_k(s) \geq 1$, and 0 otherwise. The first term denotes the total reward collected by all users, where the reward $V_k$ of a task $k$ is collected if at least one user executes the task successfully (i.e., $M_k(s) \geq 1$). The second term denotes the total cost incurred on all users. Formally, the socially efficient solution $s^o$ is given by:

$$s^o \triangleq \arg \max_s W(s)$$

s.t. $s_i$ satisfies (2)-(4), $\forall i \in \mathcal{N}$.

(15)

By comparing $W(s)$ in (14) and $\Phi(s)$ in (12), we can see that both functions have the similar structure, except the coefficients for $V_k$, $k \in S$ in the first term, i.e., $\sum_{m=1}^{M_k(s)} \frac{1}{m}$ and $1_{M_k(s) \geq 1}$. We can further see that

$$\sum_{m=1}^{M_k(s)} \frac{1}{m} \geq 1_{M_k(s) \geq 1},$$

where the equality holds only when $M_k(s) = 1$ (both sides are 1) or 0 (both sides are 0). Namely, the coefficient for each $V_k$ in $\Phi(s)$ is no smaller than that in $W(s)$. This implies that for any task, users are more likely to execute the task at the NE than SE. This leads to the following observation.

Observation 1. The task selections at the NE, especially that resulting from (13), are more aggressive, comparing with those at the SE resulting from maximizing $W(s)$.

V. SIMULATIONS

A. Simulation Setting

We choose a 5km x 5km region in London as the simulation area, where tasks and users are randomly distributed in the area. We simulate a time period of 2 hours, e.g., [10:00, 12:00], within which each task is initiated randomly and uniformly. The task valid (survival) time of each task is selected randomly according to the (truncated) normal distribution with the expected value of 30 minutes. Each task needs to be started (but not necessarily to be completed) within its valid time period. The reward of each task is selected randomly according to the (truncated) normal distribution with the expected value of $\$10$ (in dollar). In the simulations, we fix the number of tasks to 8, while change the number of users from 2 to 20 (to capture different levels of competition among users).

We consider three types of different users according to their travelling modes: (i) Walking users, who travel by walking, with a relatively low travelling speed 5km/h and cost $0.2$/km; (ii) Bike users, who travel by bike, with a medium travelling speed 15km/h and cost $0.5$/km; and (iii) Driving users, who travel by driving, with a relatively high travelling speed 45km/h and cost $1$/km. Each user takes on average 10 minutes to execute a task, incurring an execution cost of $\$1$ (in dollar) on average. Both the execution time and cost follow the (truncated) normal distribution as other parameters.

B. Social Welfare Gap

We first show the social welfare gap between the NE and SE, which captures the efficiency loss of the NE.

Figure 2 presents the expected social welfare under SE and NE with three different types of users. In the first subfigure (a), users are walking users with low travelling speed and cost. In the second subfigure (b), users are bike users with medium travelling speed and cost. In the third subfigure (c), users are driving users with high travelling speed and cost. From Figure 2, we have the following observations:

1) The social welfare under SE always increases with the number of users in all three scenarios (with walking, bike, and driving users). This is because with more users, it is more likely that tasks can be executed by lower cost users, hence resulting in a higher social welfare.
2) The social welfare under NE decreases with the number of users in most cases. This is because with more users, the competition among users becomes more intensive, and the probability that multiple users choosing the same task increases, which will lead to a higher total execution/travelling cost and hence a lower social welfare.

3) The social welfare under NE may also increase with the number of users in some cases. For example, in scenario (a) with walking users, when the number of walking user is small (e.g., less than 5), the social welfare under NE increases with the number of users slightly. This is because the walking users often have a limited serving region due to the small travelling speed, hence there is almost no competition among users when the number of users is small. In this case, increasing the number of users will not introduce much competition among users, but increase the probability that the tasks being executed by lower cost users, hence resulting in a higher social welfare.

C. Social Welfare Ratio

Figure 3 further presents the social welfare ratio between NE and SE with three different types of users. We can see that in all three scenarios, the social welfare ratio decreases with the number of users. This is because the social welfare increases with the number of users under SE, while (mostly) decreases with the number of users under NE, as illustrated in the previous Figure 2. We can further see that the social welfare ratio with walking users is higher than those with bike users and driving users. This is because the competition among walking users is less intensive than that among bike/driving users, due to the limited traveling speed and serving region of walking users. Hence, the degradation of social welfare under NE (comparing with SE) is smaller with walking users. More specifically, we can find from Figure 3 that when the number of users changes from 2 to 20, the social welfare ratio decreases from 95%, 85%, and 75% to approximately 30% for walking, bike, and driving users, respectively.

VI. CONCLUSION

In this work, we study the task scheduling in the user-centric PS system by using a game-theoretic analysis. We formulate the strategic interaction of users as a task scheduling game, and analyze the NE by using a potential game. We further analyze the efficiency loss at the NE under different situations. There are several interesting directions for the future research. First, our analysis and simulations show that the social efficiency loss at the NE can be up to 70%. Thus, it is important to design some mechanisms to reduce the efficiency loss. Second, the current model did not consider the different efforts of users in executing a task. It is important to incorporate the effort into the user decision.

REFERENCES

[1] N.D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A.T. Campbell, “A Survey of Mobile Phone Sensing,” *IEEE Communications Magazine*, 48(9), 2010.
[2] R. K. Ganti, F. Ye, and H. Lei, “Mobile Crowdsensing: Current State and Future Challenges,” *IEEE Communications Magazine*, 49(11), 2011.
[3] H. Ma, D. Zhao, and P. Yuan, “Opportunities in Mobile Crowd Sensing,” *IEEE Communications Magazine*, 52(8), 29-35, 2014.
[4] WeatherLab, http://www.weatherlab.com/.
[5] Intel Urban Atmosphere, http://www.urban-atmospheres.net/.
[6] OpenSignal, http://opensignal.com/.
[7] Waze: Free GPS Navigation with Turn by Turn, https://www.waze.com/.
[8] D. Yang, G. Xue, X. Fang, and J. Tang, “Crowdsourcing to Smartphones: Incentive Mechanism Design for Mobile Phone Sensing,” *Proc. ACM Mobicom*, 2012.
[9] L. Duan, T. Kubo, K. Sugiyama, J. Huang, et al., “Incentive Mechanisms for Smartphone Collaboration in Data Acquisition and Distributed Computing,” *Proc. IEEE INFOCOM*, 2012.
[10] L. Gao, F. Hou, and J. Huang, “Providing Long-Term Participation Incentive in Participatory Sensing,” *Proc. IEEE INFOCOM*, 2015.
[11] T. Luo, H.-P. Tan, and L. Xia, “Profit-Maximizing Incentive for Participatory Sensing,” *Proc. IEEE INFOCOM*, 2014.
[12] C. Jiang, L. Gao, L. Duan, and J. Huang, “Exploiting Data Reuse in Mobile Crowdsensing,” *Proc. IEEE Globecom*, 2016.
[13] X. Zhang, L. Gao, B. Cao, Z. Li, and M. Wang, “A Double Auction Mechanism for Mobile Crowd Sensing with Data Reuse,” *Proc. IEEE Globecom*, 2017.
[14] C. Jiang, L. Gao, L. Duan, and J. Huang, “Scalable Mobile Crowdsensing via Peer-to-Peer Data Sharing,” *IEEE Transactions on Mobile Computing*, 2017.
[15] X. Sheng, J. Tang, and W. Zhang, “Energy-efficient collaborative sensing with mobile phones,” *Proc. IEEE INFOCOM*, 2012.
[16] Q. Zhao, Y. Zhu, et al., “Fair energy-efficient sensing task allocation in participatory sensing with smartphones, *Proc. IEEE INFOCOM*, 2014.
[17] S. He, D. Shin, J. Zhang, and J. Chen, “Towards optimal allocation of location dependent tasks in crowdsensing,” *Proc. IEEE INFOCOM*, 2014.
[18] M. H. Cheung, et al., “Distributed time-sensitive task selection in mobile crowdsensing,” *Proc. ACM MobiHoc*, 2015.
[19] Field Agent, http://www.fieldagent.net/.
[20] Gigwalk, http://gigwalk.com/.
[21] D. Monderer and L.S. Shapley, “Potential Games,” *Games and economic behavior*, 14(1), 124-143, 1996
[22] L. Gao, X. Wang, Y. Xu, and Q. Zhang, “Spectrum Trading in Cognitive Radio Networks: A Contract-Theoretic Modeling Approach,” *IEEE Journal on Selected Areas in Communications*, 29(4), 843-855, 2011.
[23] Q. Ma, L. Gao, Y.F. Liu, and J. Huang, “A Game-Theoretic Analysis of User Behaviors in Crowdsourced Wireless Community Networks,” *Proc. IEEE WiOpt*, 2015.
[24] L. Duan, L. Gao, and J. Huang, “Cooperative Spectrum Sharing: A Contract-based Approach,” *IEEE Transactions on Mobile Computing*, 13(1), 174-187, 2014.
[25] L. Gao, G. Iosifidis, J. Huang, L. Tassiulas, and D. Li, “Bargaining-based Mobile Data Offloading,” *IEEE Journal on Selected Areas in Communications*, 32(6), 1114-1125, 2014.
[26] Y. Luo, L. Gao, and J. Huang, “MINE GOLD to Deliver Green Cognitive Communications,” *IEEE Journal on Selected Areas in Communications*, 33(12), 2749-2760, 2015.
[27] L. Gao, Y. Xu, and X. Wang, “MAP: Multi-Auctioneer Progressive Auction for Dynamic Spectrum Access,” *IEEE Transactions on Mobile Computing*, 10(8), 1144-1161, 2011.
[28] Online Technical Report at arXiv, url: http://arxiv.org/abs/1708.09122