

Incentive Mechanisms for Participatory Sensing: Survey and Research Challenges

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Participatory sensing is a powerful paradigm that takes advantage of smartphones to collect and analyze data beyond the scale of what was previously possible. Given that participatory sensing systems rely completely on the users' willingness to submit up-to-date and accurate information, it is paramount to effectively incentivize users' active and reliable participation. In this article, we survey existing literature on incentive mechanisms for participatory sensing systems. In particular, we present a taxonomy of existing incentive mechanisms for participatory sensing systems, which are subsequently discussed in depth by comparing and contrasting different approaches. Finally, we discuss an agenda of open research challenges in incentivizing users in participatory sensing.

Categories and Subject Descriptors: C.2 [Computer Systems Organization]: Computer-Communication Networks

General Terms: Participatory Sensing, Incentive

Additional Key Words and Phrases: QoI, game theory, auction theory, research challenges, survey

ACM Reference Format:

Francesco Restuccia, Sajal K. Das, and Jamie Payton. 2016. Incentive mechanisms for participatory sensing: Survey and research challenges. *ACM Trans. Sen. Netw.* 12, 2, Article 13 (April 2016), 40 pages.

DOI: <http://dx.doi.org/10.1145/2888398>

1. INTRODUCTION

Recent smartphones are equipped with a plethora of embedded multimodal sensors and integrate wireless communication technologies as well as complex processing capabilities. These technological features, coupled with the widespread usage of smartphones [Cisco 2014], have contributed to the emergence of applications based on a new and promising paradigm known as participatory sensing.¹ The main idea behind participatory sensing is to enable ordinary citizens (or users) to actively monitor various

¹For the sake of generality, in this article we use the term *participatory sensing* to designate applications where participants voluntarily contribute sensor data for their own benefit and/or the benefit of the community by using their phones. Such a notion therefore includes mobiscopes [Abdelzaher et al. 2007], opportunistic sensing [Campbell et al. 2006], and equivalent terms such as *mobile phone sensing*, *smartphone sensing* [Lane et al. 2010], or *crowdsensing*. It also covers specific terminologies focusing on particular monitoring subjects, such as *urban sensing* [Campbell et al. 2006], *citizen sensing* [Burke et al. 2006], *people-centric sensing* [Campbell et al. 2006, 2008], and *community sensing* [Krause et al. 2008].

This work was supported by the National Science Foundation under grants IIS-1404673, CNS-1404677, IIP-1540119, CNS-1545050.

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DOI: <http://dx.doi.org/10.1145/2888398>

phenomena pertaining to themselves (e.g., health, social connections) or their community (e.g., environment). For example, the cameras on smartphones can be used as video and image sensors [Bao and Roy Choudhury 2010], the microphone can be used as an acoustic sensor [D'Hondt et al. 2013], and the embedded global positioning system (GPS) receiver can be used to gather accurate location information, whereas gyroscopes, accelerometers, and proximity sensors can be used to extract contextual information about the user (e.g., if the user is driving [Nawaz and Mascolo 2014]). Furthermore, additional sensors can be easily interfaced with the phone via Bluetooth or wired connections (e.g., temperature sensors [Thermodo 2014]). Real-life applications, which can take advantage of both low-level sensor data and high-level user activities, range from real-time traffic monitoring applications like Nericell [Mohan et al. 2008] or Waze [Waze 2014] to air pollution monitoring [Méndez et al. 2011] and social networking [Miluzzo et al. 2007]. For an excellent survey of applications based on the participatory sensing paradigm, please refer to Khan et al. [2013].

Although a clear consensus on the best architecture for participatory sensing systems has not yet been reached, the majority of the existing participatory sensing applications utilize a centralized cloud-based architecture. In particular, volunteers use mobile phones to collect sensor data and submit (via wireless data communication links) to a participatory sensing platform (PSP) located in the cloud. The sensing tasks on the phones can be triggered manually, automatically, or based on the current context [Christin et al. 2011]. On the PSP, the data is analyzed and made available in various forms, such as graphical representations or maps showing the sensing results at an individual or community scale. The results may be displayed locally on users' mobile phones or accessed by the broader public through Web portals, depending on the application needs.

Participatory sensing provides a significant number of advantages with respect to previous sensing paradigms:

- The lack of a fixed sensing infrastructure dramatically eases deployment and maintenance costs associated with the administration of the participatory sensing system.
- The sheer number of smartphone users, coupled with the ubiquitousness of WiFi and 3/4G cellular-based Internet connectivity, allows a level of spatiotemporal sensing coverage impossible to achieve in previous paradigms, including wireless sensor networks.
- The presence of people in the sensing loop provides the opportunity to acquire *opinions* along with sensor data, allowing the emergence of complex mobile applications such as real-time traffic monitoring [Thiagarajan et al. 2009; Waze 2014; Zhou et al. 2014].
- The widespread availability of software development tools and markets for smartphone applications (apps) makes development and distribution of participatory sensing software relatively easy.

The most distinctive characteristic of participatory sensing is that it relies completely on the voluntary commitment of participants to submit up-to-date and reliable information to the PSP. This implies that a key factor for the success of participatory sensing applications is incentivizing users' active participation in the sensing surveys. To this end, several incentive mechanisms, mostly based on game theory [Tadelis 2013] and auction theory [Krishna 2009], have been proposed to increase not only the collected amount of data but also its quality. The underlying idea of such incentive mechanisms is to reward users depending on their contribution to the participatory sensing campaign. For example, rewards made may be based on submitting a report close to a desirable location [Jaimes et al. 2012], how a report contributes to social welfare [Luo

and Tham 2012; Tham and Luo 2014], the number of reports that a user sent, or the time dedicated to collecting and submitting sensing reports [Yang et al. 2012].

However, several research issues regarding incentivizing users in participatory sensing systems still remain. For example, the best way to incentivize users in participatory sensing is unclear. In particular, whereas some people may respond to a monetary reward to participate, others may still be willing to participate for free, provided they receive sufficient value by gaining access to the crowdsensed data that is shared via the participatory sensing system. Thus, understanding the reasons that drive individuals to participate in participatory sensing campaigns could lead to designing more effective incentive mechanisms. Another challenge to overcome is the fact that participatory sensing apps may access particularly sensitive information, such as the visited locations of users, as well as personal multimedia data like photos and video. This may significantly discourage participation to the sensing campaigns, regardless of the amount of incentive put forth [Albers et al. 2013; Krontiris et al. 2010]. Furthermore, most existing incentive mechanisms reward users irrespective of the quality of the information contained in the reports, which may undermine information reliability and encourage abuse of the system by malicious participants [Restuccia and Das 2014]. Therefore, designing mechanisms that are able to estimate and enforce information quality becomes of primary importance. However, enforcing quality of information (QoI) in participatory sensing is extremely challenging due to the possible presence of unreliable humans in the sensing loop. These and other research challenges still need to be analyzed and discussed—and this motivates our work.

Within the scope of this article, we analyze the state of the art in incentive mechanisms as applied to participatory sensing campaigns; besides describing the solutions currently applied, we also highlight their limitations and discuss open issues as well as their impact on participation of users in sensing surveys. Specifically, our contributions can be summarized as follows:

- We propose a taxonomy of existing incentive mechanisms for participatory sensing systems.
- For each component of the taxonomy, we discuss and analyze existing incentive mechanisms.
- Based on this analysis, we identify and discuss an agenda of open research challenges that must be addressed to support widespread participation of users in sensing campaigns.

These contributions are presented as follows. Section 2 briefly describes the concept of participatory sensing, whereas Section 3 introduces background concepts on motivation theory and work on incentivization in fields different from participatory sensing. In Section 4, we introduce a taxonomy of existing incentivization mechanisms for participatory sensing. Sections 5, 6, and 7 present an overview and an analysis of existing incentives as they relate to the organizational structure of the taxonomy. In Section 8, we discuss open research challenges before concluding the article in Section 9 with directions of future work.

2. WHAT IS PARTICIPATORY SENSING?

Participatory sensing [Burke et al. 2006] is a novel paradigm that leverages the widespread use of smartphones to acquire up-to-date and fine-grained information about a location (or event) of interest. As depicted in Figure 1, most existing participatory sensing systems are generally organized into an architecture where the main components are the *users*, the *sensing application* (app), and the PSP:

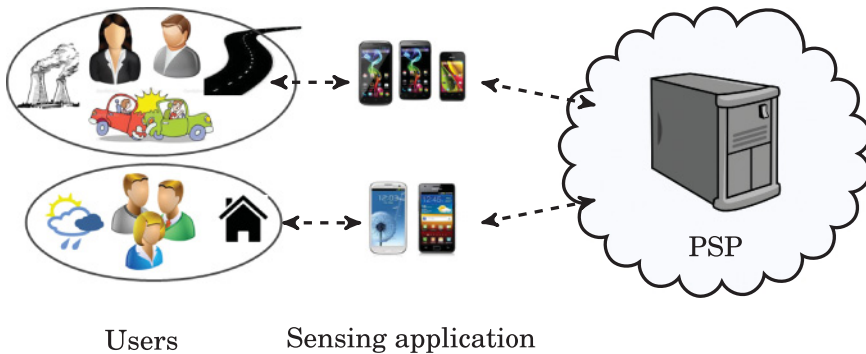


Fig. 1. Participatory sensing architecture.

- The main component of the system is the *users*, whose task is to use their smartphones (particularly the sensing application) to capture different kinds of sensor data, such as location, images, sound samples, accelerometer data, biometric data, and barometric pressure. However, *opinions* about the sensing area or an environmental phenomenon, such as traffic status or weather information, may also be provided by the users. In practical implementations of participatory sensing systems, users typically register with the system by providing a username and password [Waze 2014] that allows their contributions to be uniquely identified.
- The *sensing application* (app), deployed on users' smartphones, is distributed through common application markets, like Google Play or App Store, or is retrieved from a mobile cloud computing system [Fakoor et al. 2012]. It is responsible for providing users with a friendly user interface for data acquisition and visualization. In particular, data acquisition may be triggered by users themselves or may be elicited by the app on a one-time on-demand basis or periodically.
- The backend component of the system is the PSP, responsible for the filtering, elaboration, and redistribution of sensed data, as well as coordinating every operation performed by the system. This component is usually implemented by a set of servers dedicated to the processing of sensed data [Restuccia and Das 2014]. The PSP also ensures efficient storage and elaboration of the sensed data coming from the users, which may be stored in relational databases [Gaonkar et al. 2008] or databases specially adapted to the management of sensor readings, such as *sensedDB* [Grosky et al. 2007]. Along with the main elaboration system, the PSP might leverage a *reputation system* and an *incentive mechanism*. Briefly, the target of a reputation system is to predict the reliability of the data sent by users based on their past behavior [Wang et al. 2013; Huang et al. 2010] so as to filter out unreliable reports. Conversely, the target of an incentive mechanism is to encourage participation of users by appropriately rewarding users for their contributions to the participatory sensing campaign. The detailed discussion of such incentive mechanisms is the focus of this article.

3. BACKGROUND

In this section, we introduce relevant background on motivation theory, and we briefly discuss incentivization mechanisms in other application domains.

Understanding the motivations that drive human beings to perform actions or tasks has been the object of abundant research, especially in the domain of psychology [Elliot and Covington 2001; Maehr and Meyer 1997; Maslow 1943]. In this context, the term *motivation* is used to describe the representation of the reasons for our actions, our

desires, and our needs [Pardee 1990]. Motivation can be divided into two different categories: *intrinsic* and *extrinsic* motivation:

- Intrinsic motivation can be defined as the self-desire to seek out new experiences and new challenges, to analyze one’s capacity, to observe, and to gain knowledge [Ryan and Deci 2000b]. It is driven by an interest or enjoyment in the task itself and exists within the individual rather than relying on external pressures or a desire for reward. For example, a student may have intrinsic motivation when believing that he has the skills to be effective in reaching desired goals in a course [Ryan and Deci 2000a]. Intrinsic motivation is a natural motivational tendency and is a critical element in cognitive, social, and physical development.
- Extrinsic motivation refers to the performance of an activity to attain a desired outcome [Ryan and Deci 2000b]. It comes from influences outside of the individual and is usually used to attain outcomes that a person would not get from intrinsic motivation. Common extrinsic motivations are rewards (e.g., money, prizes, recognition) for showing the desired behavior. Competition is considered to be an extrinsic motivator because it encourages the performer to win instead of simply enjoying the intrinsic rewards of the activity [Ryan and Deci 2000a].

In motivation theory, an *incentive* is defined as something that motivates an individual to perform an action. The study of incentive structures is central to the study of all economic activities, both in terms of individual decision making and in terms of cooperation and competition within a larger institutional structure [Armstrong and Stephens 2005]. Incentives can be classified as either *positive* or *negative*. Positive incentives seek to motivate others by promising a reward, whereas negative incentives aim to motivate others by threatening a punishment. Incentives can be classified according to the different ways in which they motivate agents to take a particular course of action. A well-known taxonomy [Dalkir 2013] divides incentives into four broad classes:

- Remunerative*: Such incentives provide an agent with a form of material reward (e.g., money) in exchange for acting in a particular way.
- Moral*: A moral incentive describes the appeal of a particular choice or activity that is widely regarded as “the right thing to do,” or as particularly admirable, or where the failure to act in a certain way is condemned as indecent. A person acting on a moral incentive can expect a sense of self-esteem and approval or even admiration from his community.
- Natural*: Similarly to intrinsic motivations, natural incentives may be curiosity, mental or physical exercise, admiration, fear, anger, pain, joy, or the pursuit of truth, or the control over things in the world or people or oneself.
- Coercive*: A coercive incentive describes the case when the failure to act in a particular way will result in punishment being used against her by others in the community, such as by inflicting pain in punishment, or by imprisonment, or by confiscating or destroying their possessions.

3.1. Related Work on Incentivization Mechanisms

There have been many investigations of the incentive issues in the broader area of crowdsourcing, which is defined as the process of obtaining needed services, ideas, or content by soliciting contributions from a large group of people, and especially from an online community, rather than from traditional employees or suppliers. Zhang and van der Schaar [2012] proposed reputation-based incentive mechanisms for crowdsourcing, where participants will earn reputations upon the completion of a task. Kamar and Horvitz [2012] designed incentive mechanisms for consensus tasks that have correct answers to incentivize users for reporting true information. They introduced a novel

payment rule, called the *consensus prediction rule*, for evaluating users' reports to determine the payments. Nath et al. [2012] focused on incentive mechanisms designed to minimize the total cost or minimize the total time for executing the task. However, they considered sybil proofness, budget balance, contribution rationality, and collapse proofness but not truthfulness. Singla and Krause [2013] presented a novel, no-regret posted price mechanism in stochastic online settings. Using a different approach, Goel et al. [2014] proposed a truthful mechanism, TM-Uniform, for crowdsourcing markets with a budget constraint. They proved that TM-Uniform is budget feasible, individually rational, and truthful, and is 3-approximate compared to the optimum solution. However, they assumed that each user is only allowed to work on one task. Therefore, the task assignment process is basically a matching between tasks and users. Incentive mechanism design was also studied for problems more related to the networking field, such as spectrum trading [Yang et al. 2014] and cooperative communications [Chen et al. 2011], among others.

The design of incentive mechanisms for participatory sensing systems is particularly challenging and differentiates from the aforementioned forms of incentive mechanism design. Specifically, as participants move over the sensing area and submit reports through mobile devices, the *quality* of their sensing contributions changes dynamically and significantly over time. The quality of sensing reports and their value for the participatory sensing system also strongly depend on the *location* of the participant. For example, a traffic report submitted from a not particularly important location or delayed by several minutes might not be of much value for the system. The selection and reward assignment processes must therefore reflect this aspect, which has been neglected in most existing mechanisms.

4. OVERVIEW OF INCENTIVE MECHANISMS IN PARTICIPATORY SENSING

In this section, we first identify the main components of the sensing and incentivization process of existing systems. We then propose a taxonomy of incentive mechanisms for participatory sensing, which will be used to organize a detailed discussion of the state of the art in the following sections.

Figure 2 depicts the main activities of the sensing and incentivization processes in a participatory sensing system. Since this collection of activities is performed again and again over the lifetime of the participatory sensing campaign, henceforth we will use the term *sensing round* to refer to the execution of the following four steps:

- (1) *Sensing task advertisement*: In this phase, the PSP communicates to the users the list of sensing tasks that need to be executed during the current sensing round. In particular, each sensing task specifies a series of requirements, such as the sampling rate requested [Koutsopoulos 2013], minimum sensing time [Ji and Chen 2014], maximum distance from specified location [Ueyama et al. 2014], or task expiration time [Li and Cao 2013; Zhao et al. 2014]. For example, a sensing task might be "report the current traffic status near the Golden Gate bridge by 5:00 PM." Additional parameters may be sent, such as QoI requirements [Albers et al. 2013; Liu et al. 2011]. Sensing tasks can be advertised statically [Yang et al. 2012; Feng et al. 2014a; Duan et al. 2014] or dynamically [Restuccia and Das 2014; Feng et al. 2014b]. In some cases, depending on the application, tasks can be retrieved by users asynchronously, such as each day [Li and Cao 2014], or whenever requested by participants [Li and Cao 2013].
- (2) *Private information disclosure*: After the advertisement of the sensing tasks, the PSP collects information about the participating user, often called the *type* [Yang et al. 2012] of the user, which can be leveraged by the PSP to make a choice regarding the scheduling of sensing tasks. For example, users may supply a *bidding value*,

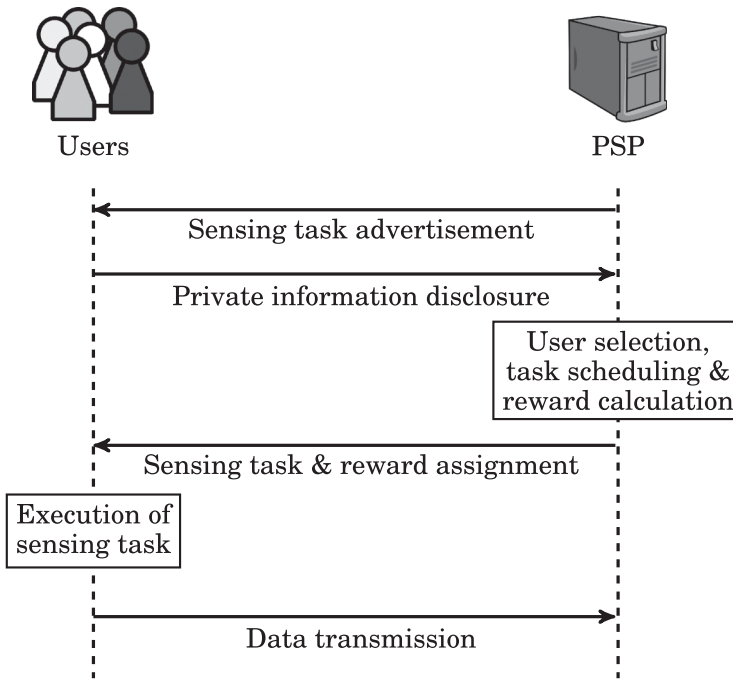


Fig. 2. Sensing and incentivization activities within a sensing round.

which is included in the user type for use in auction-based incentive mechanisms. The PSP may collect temporal information about the user, which can be used to determine the user's availability to perform sensing services [Han et al. 2013]. The PSP may also acquire information regarding the characterization of the skills of a person [Luo et al. 2014b, 2014c] and the incurred cost for the required sensing services, such as privacy loss [Duan et al. 2012], energy consumption, or mobile data charges [Luo and Tham 2012].

- (3) *User selection, task scheduling, reward calculation, and assignment*: After receiving private information describing the users, the PSP selects a subset of users who will submit the sensed information to the PSP and schedules the sensing tasks for users. For example, users might be selected according to their geographical position [Ma et al. 2014; Feng et al. 2014a; Zhang et al. 2014] or according to the submitted bid [Yang et al. 2012], cost of sensing services [Duan et al. 2014], or sensing effort [Luo et al. 2014b]. Furthermore, the PSP may schedule the sensing tasks according to the temporal availability of the users [Chen and Wang 2013; Feng et al. 2014b]. In this phase, the users are also rewarded for their services, usually according to the time dedicated to the sensing services. The information quality contained in sensing reports might also be a parameter to decide the amount of reward to assign to users [Restuccia and Das 2014]. User selection, task scheduling, and reward assignment algorithms are an important part of incentive mechanisms and are a focus of our analysis of the state of the art in Sections 5, 6, and 7.
- (4) *Execution of sensing task and data transmission*: After being selected and instructed on the sensing task to execute, a user is allowed to begin performing the sensing service using the sensing application. The sensing application may be designed to assist in collecting data according to one of the following sensing modes: manual, automatic, or context aware [Christin et al. 2011]. In the *manual*

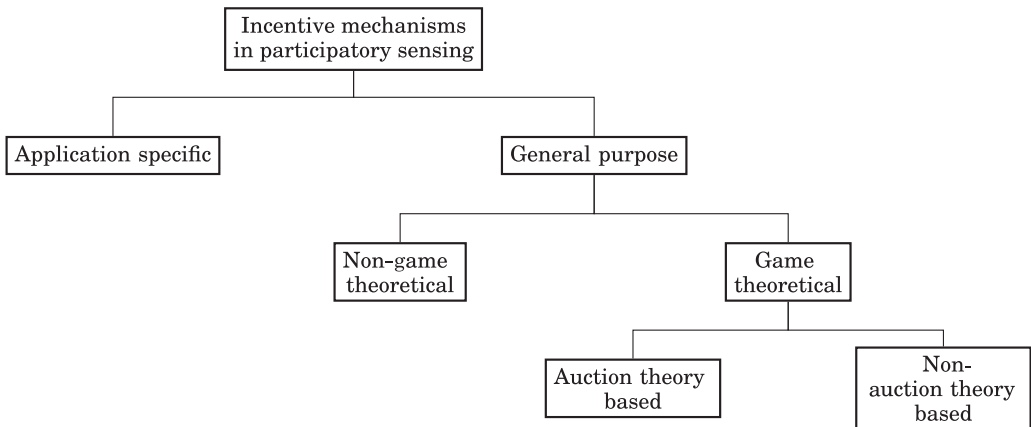


Fig. 3. Taxonomy of existing incentive mechanisms.

mode, the participants explicitly trigger the collection of sensor readings when they detect what they perceive to be relevant events, such as traffic congestion. On the contrary, the participants are not directly involved in the *automatic* mode (also known as opportunistic sensing [Khan et al. 2013]), where a sensing application continuously runs in the background and regularly sends the sensed information to the PSP, such as in Nericell [Mohan et al. 2008]. Data collection might also be triggered by leveraging the *context*, occurring upon the detection of an event or condition (e.g., clapping of hands, as in the work of Bao and Roy Choudhury [2010]). The sensing application handles the transfer of the sensed data from the smartphone to the PSP, making use of communication infrastructure available to the mobile phone, such as WiFi or 3G/4G connectivity. For example, the sensor readings can be transmitted to the server using SMS or TCP connections [Gaonkar et al. 2008], remote procedure calls [Miluzzo et al. 2007], or Web interfaces [Fakoor et al. 2012]. Recently, opportunistic forwarding coupled with data fusion has been proposed as a viable method for data transmission [Ma et al. 2014].

4.1. Taxonomy of Incentive Mechanisms

Figure 3 illustrates the proposed taxonomy of the approaches used for incentivizing users in participatory sensing. The taxonomy first differentiates existing work based on the *purpose* of the mechanisms; specifically, the first distinction is made between *application-specific* and *general-purpose* incentive mechanisms. This distinction is necessary, as the former are ad hoc mechanisms proposed as a part of the participatory sensing system and are tailored to incentivize users' participation to the specific application only; in other words, they are not designed in a way that is generalizable for broader application. On the other hand, the latter are mechanisms that do not assume any particular participatory sensing application but instead are general in purpose and can be applied to a wide spectrum of systems satisfying the assumptions of the mechanism. As of yet, the majority of the mechanisms proposed have been in the general-purpose category.

Among the general-purpose mechanisms, another distinction is made based on the *methodology* being used to incentive participation. In particular, we differentiate between *game-theoretical* approaches, which are grounded in mathematical models that provide a foundation for reasoning about rational decision making, and mechanisms that exploit different concepts, such as micropayments [Reddy et al. 2010b]. Game-theoretical approaches can be further categorized, distinguishing between mechanisms

that exploit auction theory [Krishna 2009] and mechanisms that instead use other game-theoretical concepts, such as Stackelberg games [Tadelis 2013].

In the following sections, we extensively discuss the most significant systems proposed so far in each category of the taxonomy. For each category, we will characterize the foundations of the class of participatory sensing incentive systems, review the state of the art to highlight key differentiating ideas, and analyze approaches, discussing advantages and limitations of key elements of individual approaches and, more broadly, the class of approaches.

5. APPLICATION-SPECIFIC INCENTIVE MECHANISMS

Although many participatory sensing applications have been proposed so far [Khan et al. 2013], the problem of incentivizing users' participation has been overshadowed by other design challenges, such as processing sensed data [Lane et al. 2010]. Indeed, we identified as few as three systems that include an incentivization mechanism as a first-class element of their design.

One such system is *LiveCompare* [Deng and Cox 2009], which is designed to improve interstore grocery price comparisons for shoppers. *LiveCompare* addresses the challenge of user incentivization through a simple query protocol that results in a quid pro quo interaction. When a user at a grocery store wants a price comparison for a product of interest, he uses the *LiveCompare* app installed on his mobile phone to identify the product by snapping a photograph of the product's price tag; the photo is then provided to the *LiveCompare* PSP as a price comparison query. The product of interest is uniquely identified via a barcode included on the price tag. In exchange for submitting this price data point, the user receives pricing information for the scanned product at other nearby grocery stores. The photograph provided by the user is uploaded to a central repository for satisfying future queries.

Another system that embeds an incentive in the design is *CrowdPark* [Yan et al. 2011]. This system allows users to "loosely reserve" parking spots in urban areas and is based on the interesting idea that an individual who is currently parked can provide notification in advance about when she plans to leave. This information may be *sold* to a buyer who is willing to pay to reserve the parking spot. This simple protocol for drivers to buy and sell information about parking vacancies acts as an incentive mechanism for both buyers and sellers of parking information. The authors point out two interesting concepts when designing the *CrowdPark* incentive. In particular, they remark that the incentive mechanism should take into account the "utility" of a transaction—that is, bonuses should be provided when a transaction leads to successful acquisition of a parking spot, and refunds should be provided when unsuccessful. However, on the other hand, there is also need to handle *malicious users*, whose goal is solely to maximize their monetary gain either by masquerading as fake sellers or by denying successful reservations to obtain a refund. To this end, the authors proposed a simple game-theoretical design of the parking reservation rules ensuring that buyers maximize their gain by telling the truth. The key idea behind the approach is that a buyer who successfully parks at a reserved spot can resell that spot through *CrowdPark* if he tells the truth. If he denies a successful instance of parking in a reserved spot, obviously he cannot resell this spot. Therefore, if reward parameters are set to ensure that the average gain of reselling is higher than the gain by lying and receiving a refund, a rational user will be inclined toward telling the truth. The extended problem formulation was extended by the same authors in Hoh et al. [2012] and analyzed by using Amazon Mechanical Turk (AMT) [Amazon 2014] as the experimental platform. They recruited 131 participants and designed a Web-based survey that replicates the actual scenario of consumer confirmation. Results indicate that the proposed methodology drives users toward cooperative behavior.

To the best of our knowledge, the only other participatory sensing application to include an incentive mechanism as a key part of the system design is *Waze* [Waze 2014]. In particular, the reward strategy of *Waze* leverages the concept of “gamification” [Deterding et al. 2011] to engage users and encourage them to provide more information without the need for monetary incentives. For example, it allows drivers to “drive over” icons of cupcakes and other objects to earn points. *Waze* also uses a point-based system to rank users based on their level of participation. Specifically, *Waze* offers points for traffic or road hazard reports, which can be used to change the user’s avatar and to increase their status in the community. Users have their own personal “dashboard” where their ranking among worldwide users is shown. There is also a leaderboard, which shows who has accrued the most points overall, who has driven the most miles over the week, or who has filed the most reports [Furchgott 2010]. The concept of gamification as applied to participatory sensing has also been recently explored in Ueyama et al. [2014] and will be detailed in Section 6 as a non-game-theoretical mechanism to incentivize user participation.

5.1. Discussion

The incentivization methods that have been proposed as part of the LiveCompare [Deng and Cox 2009] and CrowdPark [Yan et al. 2011] systems make strong assumptions that ultimately limit the applicability of the proposed mechanisms. For example, the effectiveness of the approach proposed in LiveCompare has not been validated through a systematic user study or mathematical analysis. In particular, since the study of LiveCompare relied on a user survey through AMT rather than a deployment that required users to perform the sensing task [Deng and Cox 2009], it is unclear if a *quid pro quo* scheme in which users receive information from the PSP (e.g., receiving price information at nearby stores for a product of interest) is enough of an incentive for a user to perform high-burden sensing tasks (e.g., taking photos for a significant number of items while grocery shopping).

Furthermore, the CrowdPark approach, proposed in Yan et al. [2011] and extended in Hoh et al. [2012], assumes that mobile phones are trustworthy, and therefore a malicious user cannot manipulate location coordinates intentionally when reporting the location and availability of a parking space. However, it is well known that users can easily spoof GPS coordinates by using widely available applications such as *FakeLocator*, available for both iOS- and Android-based smartphones. This piece of software is able to change the current GPS position of users by hijacking the communication between the smartphone location interfaces and applications accessing the location data [Restuccia and Das 2014]. For example, *FakeLocator* acts as an additional location provider that takes a higher priority than all others, forcing the Android system to distribute the fake location that it is advertising. The user can then specify any location on Earth to *FakeLocator* and let the other apps in the smartphone “believe” that the user is in that location. Hereafter, we refer to this kind of malicious behavior as a location-spoofing attack. Figure 4 depicts the functioning scheme of *FakeLocator* and an example of a location-spoofing attack.

Waze has proven to be effective in incentivizing user participation, as more than 50 millions users participate daily as users of and contributors to the traffic map [Yahoo! 2012]. However, the gamification incentive used by *Waze* is also prone to the location-spoofing attack, as the system is not able to recognize between genuine and compromised users. This vulnerability of *Waze* was also demonstrated by a large-scale attack in which a fake traffic jam was injected into the system [Atherton 2014]. Therefore, the game-based incentive system can be compromised by malicious users, who can continue to earn points through the gamification incentive without actually performing any sensing tasks of value.

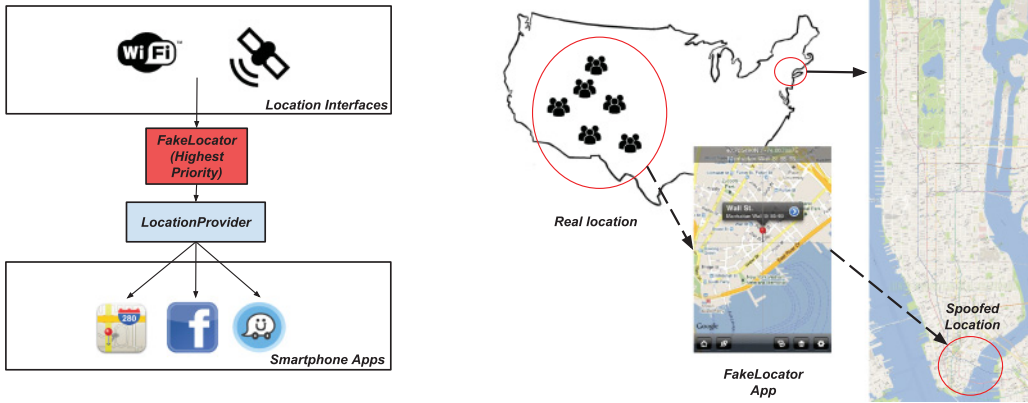


Fig. 4. Functioning scheme of FakeLocator and a location-spoofing attack.

Table I. Summary of Non-Game-Theoretical-Based Incentive Mechanisms

Work	Key Contribution	QoI	Resources	Privacy
Cheung et al. [2014]	Resource-aware incentive mechanism	×	✓	×
He et al. [2015]	Recruitment framework for vehicle-based crowdsourcing	✓	×	×
Kawajiri et al. [2014]	Gamification-based mechanism	✓	×	×
Li and Cao [2014]	Two privacy-preserving incentive mechanisms	×	✓	✓
Li and Cao [2013]	Privacy-aware incentive mechanism including multiple user contributions	×	×	✓
Li et al. [2015]	QoI-aware recruitment framework	✓	×	×
Liu et al. [2011] and Liu et al. [2014]	QoI-aware and energy-efficient incentive framework	✓	✓	×
Luo et al. [2014a]	Endorsement-based incentive mechanisms through Web relations	✓	×	×
Mukherjee et al. [2014]	Incentive mechanism based on types and priorities of events, quality and timeliness of reports, and user intent	✓	×	×
Reddy et al. [2010a]	User selection based on spacial and temporal availability, as well as participation habits	✓	×	×
Reddy et al. [2010b]	Micropayments-based mechanism	✓	×	×
Ren et al. [2014]	Social impact and trustworthiness of users	✓	×	×
Restuccia and Das [2014]	Trust-based framework based on mobile security agents (MSAs)	✓	×	×
Song et al. [2014]	QoI-aware incentive mechanism with budget constraints	✓	×	×
Tarable et al. [2015]	Reputation-based recruitment mechanism	✓	×	×
Tham and Luo [2013, 2015]	Incentive mechanism with novel definition of quality of contributed service and market equilibrium	✓	×	×
Ueyama et al. [2014]	Gamification-based mechanism	×	×	×
Zhang et al. [2014]	Recruitment framework with budget constraints	✓	×	×

6. NON-GAME-THEORETICAL INCENTIVE MECHANISMS

This section surveys general-purpose incentive mechanisms that do not exploit game-theoretical concepts in their design. Table I summarizes the works (in alphabetical order) discussed in this section, with a brief description of the key contribution. To facilitate the discussion, we further divide the works into three categories:

- QoI-aware mechanisms*: These mechanisms take into account the QoI of each sensing report before making decisions on sensing task and reward assignment. Since QoI in participatory sensing systems has not yet been clearly defined, the characterization and assessment of QoI differ across the incentive mechanisms surveyed.
- Resource-aware mechanisms*: These mechanisms consider the resource consumption (e.g., energy, mobile cellular data) of the user in assigning sensing tasks.
- Privacy-aware mechanisms*: These mechanisms address the need to provide privacy to participating users who are exposing sensitive data.

6.1. QoI-Aware Mechanisms

For participatory sensing applications to be used as effective tools for collecting data that will be interpreted into high-level information used in decision making, it is essential to give careful consideration to the QoI that can be derived from participatory sensing data. Methods for assessing the QoI and encouraging participants to contribute data that meets QoI requirements for participatory sensing campaigns continues to emerge as an important research topic. Several definitions of QoI for participatory sensing have been put forth, including spatial coverage, temporal coverage, and timeliness. QoI metrics for participatory sensing also focus on the quality of the provider, assessing the reputation of the participant for providing useful data as part of the participatory sensing campaign. In the following, we discuss incentive mechanisms that are designed to improve the QoI provided by users in participatory sensing systems.

6.1.1. QoI by Recruitment, Micropayments, and Reputation. To improve the QoI achieved through participatory sensing, Reddy et al. [2010a] proposed a recruitment process to select participants who are likely to provide information that meet QoI requirements. In this work, QoI is defined in terms of the ability to collect a crowdsensed dataset that meets spatial and temporal coverage requirements. As such, the system considers availability predictions of volunteers for recruitment of participants, and their reputations are introduced for incentivization. In detail, the system relies on three steps to select the users:

- Qualifier*: Participants must meet minimum requirements, such as destinations and routes within time, space, and transportation mode constraints.
- Assessment*: Once participants who meet minimum requirements are found, the recruitment system then identifies which subset of individuals maximize coverage over a specific area and time period while adhering to the required transportation modes.
- Progress review*: As a campaign runs, the recruitment system must check participants' coverage and data collection reputation to determine if they are consistent with their profile.

To build the reputation score of users, the authors use sampling likelihood, as well as assessments of quality and validity of a user's contributions over several campaigns or by campaign-specific calibration exercises. In particular, they use a beta function-based algorithm to calculate the reputation, using the the correct and incorrect sensing reports as α and β parameters, respectively. The authors demonstrate the application of the framework by analyzing data from a pilot mobility study of 10 users.

Similarly, Zhang et al. [2014] propose *CrowdRecruiter*, a framework that aims to minimize incentive payments by selecting a small number of participants while satisfying a QoI requirement framed as a *probabilistic* spatiotemporal coverage constraint. To reduce the barrier to participation, *CrowdRecruiter* leverages piggybacking on 3G phone calls to send data in an effort to minimize energy consumption on users' mobile devices. Information about the 3G connection is also used to determine how to satisfy the QoI requirement. First, the framework predicts the call and coverage probability

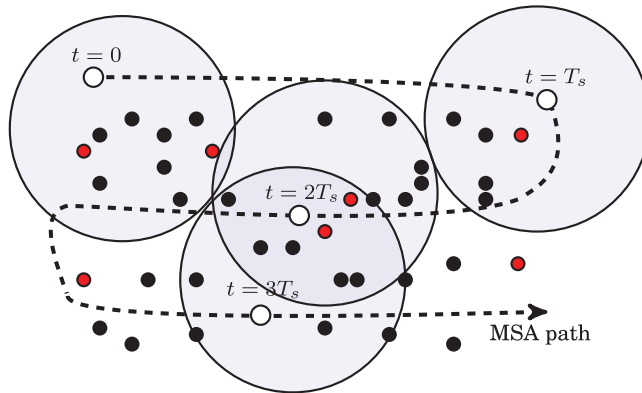


Fig. 5. An MSA roaming over the sensing area [Restuccia and Das 2014].

of each mobile user based on historical records. It then efficiently computes the joint coverage probability of multiple users as a combined set and selects the near-minimal set of participants, which meets the coverage ratio requirement in each sensing cycle.

The concept of *micropayments*, in which sensing tasks are matched with small payments, has been also proposed in Reddy et al. [2010b] as an incentive model to increase high-quality contributions from users. As the first such effort, contributions of this work include the definition of a set of metrics that can be used to evaluate the effectiveness of an incentive to motivate an individual user. The set of metrics included the quantity of submissions, an application-specific measure of the quality of data submitted, and the spatial and temporal coverage. An evaluation of the approach was performed through a pilot study using various micropayment schemes in a participatory sensing application for a university initiative; users were asked to take photos of trash bins on campus with the goal of understanding recycling habits across the campus. Results indicated that micropayments were more effective than a single lump payment for increasing quantity of submissions, application-specific quality of data (here, clear and focused images of trash bins located on the campus), and spatiotemporal diversity of submissions.

Because participatory sensing relies on the contributions of users, researchers have pointed out the potential for developing systems that identify *reliable* users [Huang et al. 2014] as a way to address QoI requirements. Although several reputation frameworks have been proposed (e.g., Christin et al. [2013b] and Wang et al. [2014]), Restuccia and Das [2014] point out that previous incentive and reputation mechanisms lack a scalable and secure method for validating the QoI of sensing reports. For this reason, they propose a novel trust-based data verification system based on the concept of *mobile security agents* (MSAs). In detail, MSAs are defined as users who periodically report information about their surroundings to the PSP and are considered to be *reliable*, which means that the information sent by MSAs is correct and reflects the real condition of the area nearby the MSA.

Figure 5 shows a sensing scenario in which only one MSA is roaming the sensing area. Legitimate and malicious users are depicted by black and red dots, respectively. Figure 5 also depicts the different locations of the MSA over time at different sensing rounds. At each sensing round, the MSA reports her sensed data to the PSP. Then, such information is used to update the reputation of the users near the MSA at that particular time. In particular, the reputation is updated only for users inside a portion of sensing area, defined as an *update area* and depicted as a blue circle in Figure 5.

Note that the purpose of the MSAs is not to tackle the issue of location spoofing, which is instead done in works such as Talasila et al. [2015] and Restuccia et al. [2015]. Instead, the MSAs are leveraged to improve the QoI by building a reputation index for each participant. Specifically, this is done by cross checking the report coming from the MSAs with that coming from the participants, and decreasing or increasing the reputation level according to the past history (i.e., current reputation level) and the QoI of the report being submitted. This approach provides benefits such as scalability and security from location-based attacks, as the location of users is not involved in computing their reputation.

Tarable et al. [2015] study the optimal task assignment problem (which can be seen as a recruitment problem) when participants' reputation estimates are available. They formulate the problem as the maximization of a monotone (submodular) function subject to Matroid constraints. As the optimal problem is NP-hard, they propose a greedy heuristic task allocation algorithm. They also propose a simple maximum a posteriori decision rule and compare different solutions, showing that system performance can greatly benefit from information about participants' reputation.

Mobility information may be leveraged to increase the QoI by selecting an appropriate subset of users. He et al. [2015] consider vehicle-based crowdsourcing, which has the distinct advantage of predictable mobility. They present a new participant recruitment strategy for vehicle-based crowdsourcing, which considers not only current location but also the future trajectories of participants. This strategy guarantees that the system can perform well using the currently recruited participants for a period of time in the future. The participant recruitment problem is proven to be NP-complete, and two algorithms are proposed—a greedy approximation and a genetic algorithm—to find the solution for different application scenarios.

Li et al. [2015] consider a dynamic participant recruitment problem where the sensing tasks are dynamic (coming in real time) and heterogeneous (having different temporal and spacial requirements). They propose an online and offline algorithm that aim at minimizing the sensing cost while maintaining a certain level of probabilistic coverage. Extensive simulations over a real-life mobile dataset confirm the efficiency of the proposed algorithms.

6.1.2. QoI by Gamification. Exploiting gamification [Deterding et al. 2011] has also been recently proposed as a viable and effective technique to incentivize users' participation and also increase QoI. Briefly, gamification is the use of game thinking and mechanics in nongame contexts to engage users in solving problems and increase users' self-contributions. Widely known examples of systems that use gamification to encourage participation are the crowdsourced programming advice platform *Stack Overflow*,² which rewards users who provide top-ranked answers; the job recruitment platform *HackerRank*,³ which presents users with coding "challenges" that relate to open positions for which employers are seeking candidates; and the participatory sensing system Waze [Waze 2014], which uses several gamification elements, including leaderboards, as incentives for providing traffic information.

With respect to participatory sensing incentives that use gamification to address QoI requirements, Kawajiri et al. [2014] proposed a framework called *Steered Crowdsensing*. The system displays points to users to motivate them to move to a specific location, which increases QoI as the spacial coverage of the sensing area is increased. The authors formalize the calculation of points paid to users by introducing a quality indicator of service in an online machine learning setting. A strong contribution of their

²<http://www.stackoverflow.com>.

³<http://www.hackerrank.com>.

work is the deployment of a crowdsensing system to test the framework. A similar approach was also proposed in Mukherjee et al. [2014], where different incentives were managed based on types and priorities of events, as well as quality and timeliness of event reports; additionally, resident intent is used to incentivize users.

Another approach that uses gamification to address QoI requirements is that of Ueyama et al. [2014], who proposed an incentive mechanism that incorporates a status-level scheme depending on earned reward points so that users with higher status can earn more reward points. They also introduced a ranking scheme among users and a badge scheme so that users are attracted by getting not only monetary reward points but also by engendering a sense of accomplishment. They then formulate the problem of sensing given points of interest (PoIs) with minimal reward points and devise a heuristic algorithm for deriving the set of users to which requests are sent and appropriate reward points are given for each request. The algorithm requires the participation probability distribution for each tuple of a user, reward points, and the burden of a sensing task. Similar to Kawajiri et al. [2014], they performed an experiment with 18 users for 30 days; results indicate that the mechanism is effective in increasing the participation of users.

6.1.3. Miscellaneous Approaches. One of the first research efforts to include QoI in the design of the incentive mechanism was that of Liu et al. [2011] (extended in Liu et al. [2014]), which presented a QoI- and energy-efficient incentive mechanism framework that maximizes the quality of sensed data with minimization of the incentive cost and energy consumption of smartphones. This is accomplished by first defining the *QoI satisfaction index*, which measures how close the received QoI is to the expected/desired quality. Then, by arguing that the reward must be assigned according to the expectation of users, they introduce in an analogous manner the *credit satisfaction index*, which measures the degree of credit satisfaction for individual smartphone users. These quantities are used as input to a mathematical model based on a *Gur Game* [Tung and Kleinrock 1993], where reward and energy loss guide the users' choice between QoI and energy efficiency.

The game proposed is represented by a nearest-neighbor discrete-time Markov chain (DTMC) of size $2M$, where the set of states are divided in "positive" (from 1 to M) and "negative" states (from $-M$ to -1). Depending on the credit and QoI satisfaction indices at timestep j , the state of the DTMC is shifted toward the right-most positive state M , which represents the maximum possible level of contribution, or toward the left-most state $-M$. If the current state at timestep j is positive (i.e., j is between 1 and M), then the user chooses to participate; otherwise, he does not. In such a way, the user autonomously chooses to participate or not depending on the desired trade-off between personal satisfaction and energy consumption.

Recently, Tham et al. [2013, 2015] also explored the problem of incentivization with QoI. They first propose a new metric called *quality of contributed service* (QCS), which characterizes the information quality and timeliness of a specific real-time sensed quantity achieved. The QCS is a cumulative time-decaying or timeliness-weighted quality of contribution: the more contributions, the higher the quality of the contributions, or the more up-to-date the contributions are in the consumable window, the higher the QCS value will be. Tham et al. also formulate a market-based framework with plausible models of the market participants comprising data contributors, service consumers, and a service provider. They analyze the market equilibrium under different conditions and obtain a closed form expression for the resulting QCS at market equilibrium. Some interesting theoretical findings are also shown, such as optimal contribution level and rate for maximizing participant payoff. An algorithm is also proposed to achieve market equilibrium.

Another interesting QoI-aware mechanism was recently proposed by Song et al. [2014]. Here, the target is to find a subset of participants whose sensor data collection can best satisfy QoI requirements of multiple concurrent tasks in both temporal and spatial dimensions by supposing a constrained budget for user reward. In particular, by defining as $u_i(\mathcal{X})$ the QoI satisfaction index (definition similar to Liu et al. [2011]) obtained for the task $i \in \mathcal{Q}$ by a subset \mathcal{X} of the set \mathcal{M} of users, and by d_m the reward demanded by user m , the problem is defined as follows:

$$\begin{aligned} &\text{Maximize: } \bar{u}(\mathcal{X}) = \{u_1(\mathcal{X}), u_2(\mathcal{X}), \dots, u_Q(\mathcal{X})\} \\ &\text{subject to: } \mathcal{X} \subseteq \mathcal{M} \text{ and } \sum_{m \in \mathcal{M}} d_m \leq C_{tot}. \end{aligned} \quad (1)$$

The authors argue that the optimization problem described in Equation (1) is multi-objective, and therefore the optimal solution may not exist. Therefore, they propose a Pareto-optimal⁴ version of the problem, which is a modified nonlinear Knapsack problem, known to be NP-complete. To solve the problem, the authors propose a dynamic participant selection strategy called *DPS*, where participants are selected based on a greedy algorithm that explicitly considers their expected amount of data collected, required QoI of multiple tasks, and users' incentive requirements under the constraint of the aggregated task budget defined in Equation (1). To estimate the amount of data collected from each user, the authors introduce a Markov-based probability model based on the historical trajectory information of a user and the initial position. This information, joint with the sensing capabilities of the users, is used to predict the expected amount of data by all participants. The performance evaluation, conducted on real mobility traces, includes a comparison between *DPS*, a random selection algorithm, and Lee and Hoh [2010b]. Results indicate that *DPS* achieves better performance than both approaches.

6.2. Resource-Aware Mechanisms

A potential barrier to user contributions in participatory sensing campaigns is the consumption of resources associated with performing sensing tasks and providing sensing reports. Research in participatory sensing is beginning to address the need for resource-aware incentive mechanisms. Cheung et al. [2014] studied the decision process of the PSP and the users in participatory sensing applications that involve photo or video transmissions, where the reporting cost through the cellular network is nonnegligible. This work differentiates from previous work in that the proposed system model assumes Markovian⁵ user mobility and WiFi availability only at predefined locations (i.e., connectivity is constrained). Data collection and user incentivization are modeled as a two-stage decision process, involving both the PSP and the users. In the first stage, the PSP announces the reward to the potential participants. Specifically, the authors propose a deadline-discounted reward scheme, where any participant who obtains measurement at its initial location $l_i(1)$ at time $t = 1$ and reports its data to the PSP at time t will be given a reward $r = \theta^{t-1} \cdot R$, where $R \geq 0$ is the initial reward and $0 < \theta \leq 1$ is a discount factor. The PSP does not grant any reward for data reported after deadline T . In the second stage, each user makes its participation and reporting decisions to maximize its expected payoff by considering its sensing cost, its transmission cost, and the reward scheme of the sensing platform. To this end, they propose an optimal

⁴A solution is Pareto optimal if it is not possible to move from that solution and improve at least one objective function without detriment to any other objective function.

⁵When the mobility is Markovian, time is divided into a set of time slots \mathcal{T} , whereas space is divided in a set of locations \mathcal{L} . The current location $l_i(t) \in \mathcal{L}$ of user i at time t can be calculated by using the location transition matrix of user i , defined as $P_i \triangleq [p_i(l'|l)]_{L \times L}$, where $p_i(l'|l)$ is the probability that user i will move to location l' in the next time slot given that she is currently at location l .

participation and reporting decision (OPRD) algorithm, which achieves the maximal user payoff.

6.3. Privacy-Aware Mechanisms

Privacy is a key concern that can potentially limit the widespread adoption of participatory sensing. The work of Li and Cao [2013] offered the first approach to simultaneously deal with incentivization of users with privacy. In this work, they proposed two privacy-aware incentive schemes for participatory sensing to promote user participation. These schemes allow each mobile user to earn credits by contributing data without leaking which data she has contributed, at the same time ensuring that dishonest users cannot abuse the system to earn unlimited amount of credits. To achieve such goals, the basic idea was to issue one *request token* for each task to each user. The user consumes the token when she accepts the task. Since she does not have more tokens for the task, it cannot accept the task again. Similarly, to satisfy the second condition, each user will be given one *report token* for each task. When the PSP receives a report, it issues *pseudocredits* to the reporting user, which can then be transformed into actual credits later on. To achieve the privacy goals, all tokens are constructed in a privacy-preserving way such that a request (report) token cannot be linked to a user and credit tokens cannot be linked to the task and report from which the token was earned. The first scheme considers scenarios where a trusted third party (TTP) is available. It relies on the TTP to protect user privacy and thus has very low computation and storage cost at each mobile user. The second scheme removes the assumption of TTP and applies blind signature and commitment techniques to protect user privacy. The ideas were extended by the same authors in Li and Cao [2014], where the problem is extended to the more general case in which sensing tasks may require multiple reports from each user (e.g., in environmental monitoring applications).

6.4. Discussion

Although the problem of simultaneously incentivizing users and guaranteeing QoI has been recently tackled by a significant amount of research, the majority of existing approaches fail to consider the impact of users that *voluntarily* submit low-quality information. In particular, only Restuccia and Das [2014] consider and tackle the location-spoofing attack described in Section 5.1. Furthermore, some assumptions in existing work oversimplify the actual complexity of estimating and enforcing information quality of sensing reports in participatory sensing systems. For example, Liu et al. [2011] and Liu et al. [2014] characterize the QoI as “the amount of information contributed by user i corresponding to the l -th QoI attribute,” which does not include any information directly related to quality, such as accuracy and timeliness of report. In addition, the proposed strategy based on a Gur Game assumes that the user will always be rational and there will be no interaction of the user with the system, which is not entirely true in most of the existing participatory sensing applications. Similarly, Tham and Luo [2013, 2015] define QoI as “the detection accuracy of the system whose information quality is reflected in the degree of confidence that an event of interest has occurred” (i.e., yes/no decision). Although this assumption makes the analysis more tractable, it restricts the scope of the incentive framework only to applications handling binary opinions. The same problem is present in the work of Reddy et al. [2010a], where the very simple approach based on beta function is unable to capture the complexity of sensing reports. The aspect of understanding and characterizing QoI is also ignored by Restuccia and Das [2014], as they assume that an MSA can always postulate a binary decision (i.e., yes or no) regarding the QoI of a report. Finally, the system proposed by Zhang et al. [2014] relies on piggy-backing crowdsensing, and therefore it may not be

achievable in practice, as it assumes that 3G cellular data submitted by participants during phone calls is available to the participatory sensing application.

On the other hand, proposed gamification- and micropayments-based incentive mechanisms still lack systems to predict the QoI that will be collected by users and are based on heuristics rather than on strong mathematical principles. Additionally, strong assumptions on how QoI is determined undermine the applicability of the proposed mechanisms. For example, Kawajiri et al. [2014] consider settings where sensory data can be continuously collected and analyzed, and sensory data arrives at regular time intervals, which is unrealistic in participatory sensing environments. As far as resource-aware systems are concerned, Cheung et al. [2014] only consider transmission cost and network availability as resource parameters and fail to consider the aspect of energy consumption in the analysis. Privacy-aware incentives proposed by Li and Cao [2013, 2014], although technically sound, do not consider the aspect of QoI and resource awareness in their design, and therefore their applicability to real-world campaigns is limited. However, the most serious limitation of existing work on resource-aware and privacy-aware incentives is the lack of validation of the systems through actual participatory sensing campaigns. In particular, experimenting with real participants could allow us to understand the real value of privacy and resource consumption for participants and therefore design more efficient and cost-effective mechanisms.

7. GAME-THEORETICAL INCENTIVE MECHANISMS

This section presents incentive mechanisms that include game-theoretical aspects in their design. First we discuss auction-based approaches, and then we focus on approaches that are based on other game-theoretical foundations. For each of these categories, it is necessary to discuss first some preliminary concepts before analyzing approaches that exploit those foundations to incentive contributions to participatory sensing campaigns.

7.1. Preliminaries on Auction Theory

Auction theory is a branch of game theory that studies how the properties of *auctions* and how people act in auction markets. Auctions are decentralized market mechanisms for allocating resources [Krishna 2009] and are particularly interesting because they may be used to sell any item (i.e., auctions are *universal*), and the outcome of the auction does not depend on the identity of the bidders (which means that auctions are *anonymous*). Auctions have extensively been used in participatory sensing and have been effective in modeling the economic interactions between the PSP and the users.

There are two types of auctions: *regular* and *reverse* auctions. Figure 6 depicts the functioning scheme of a regular and reverse auction. In regular auctions, a *seller* wants to sell an item, whereas a group of people, called *buyers* (or *bidders*), compete to buy the item by offering a *bid*. The seller then selects the highest bidder and assigns the item to her. Conversely, in reverse auctions, a single buyer offers a reward to execute a *task* (which might be a sensing task in case of participatory sensing). Multiple sellers are then able to offer bids to execute the task. As the auction progresses, the price *decreases* as sellers compete to offer lower bids than their competitors while still meeting all of the specifications of the task. The task is then assigned to the lowest bidder(s).

Auction mechanisms are often modeled mathematically. More specifically, an auction-based mechanism computes (1) an output $o = f(b_1, b_2, \dots, b_n)$, representing the outcome of the auction (who is the winner), and (2) a payment vector $p_i = (p_1, p_2, \dots, p_n)$, where $p = g(b_1, b_2, \dots, b_n)$ is the money given to the i buyer (eventually zero to every buyer except the winner).

Based on the number of objects auctioned on the market, auctions can be categorized into *single-object* and *multiobject* auctions. Among single-object auction schemes, which

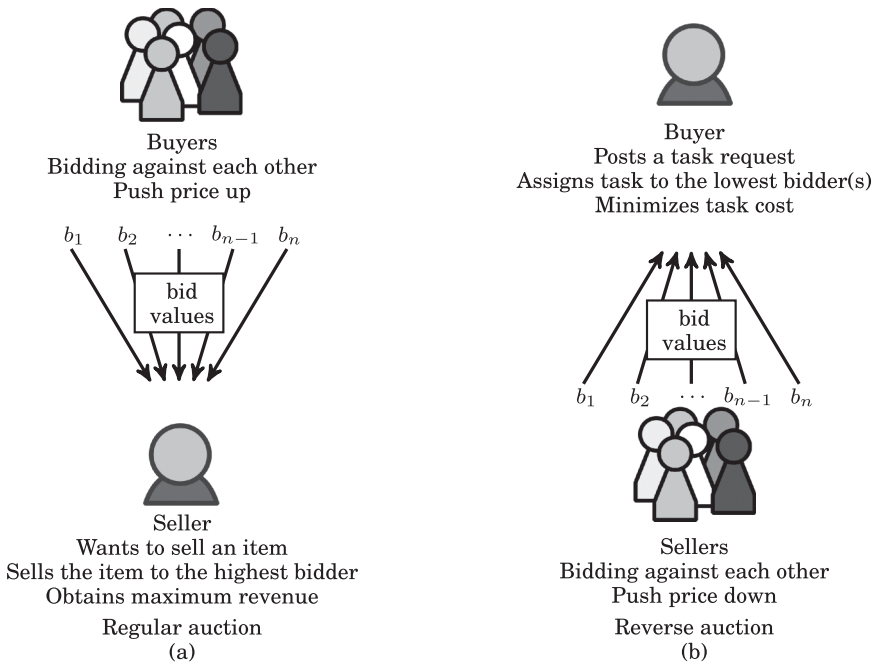


Fig. 6. Regular versus reverse auction.

are commonly applied in participatory sensing systems, the most important are *first price* and *second price*. In first-price auctions, the auctioneer grants the item to the highest bidder and charges the highest bid. In second-price auctions, the auctioneer grants the item to the highest bidder but charges the second highest bid. Another type of auction is *all-pay* auction, in which every bidder pays the proposed bid regardless of whether the bidder wins the prize, which is awarded to the highest bidder as in a conventional auction.

Four characteristics should be achieved when designing an auction-based incentive mechanism:

- Individual rationality*: Each user (or bidder) can expect a nonnegative profit.
- Truthfulness*: Revealing true private valuation is the dominant strategy for each bidder. In other words, no bidder can improve its utility by submitting a bid different from its true valuation, no matter how others submit.
- System efficiency*: An auction is system efficient if the sum of valuations of all winning bids is maximized over the possible sets of valuations.
- Computation efficiency*: The outcome of the auction, which means the set of winners among all bidders, can be computed in polynomial time.

Truthfulness of a mechanism can be guaranteed by using the following theorem.

THEOREM 1. [Singer 2010] *An auction mechanism is truthful if and only if:*

- The selection rule is monotone*: if user i wins the auction by bidding b_i , then that user also wins by bidding $b'_i \leq b_i$;
- Each winner is paid the critical value*, which means that user i would not win the auction if that user bids higher than this value.

Table II. Summary of Auction-Based Incentive Mechanisms

Work	Summary of Contributions	IR	T	SE	CE
Feng et al. [2014a]	Location-aware incentive mechanism	✓	✓	×	✓
Feng et al. [2014b]	Incentive mechanisms with dynamic sensing task arrival	✓	✓	×	✓
Gao et al. [2015]	Incentive mechanisms in offline and online bidding settings	✓	✓	×	×
Han et al. [2013]	Incentive mechanisms in offline and online bidding settings	✓	✓	×	✓
Jaimes et al. [2012]	Greedy incentive algorithm (GIA) based on RAPD	✓	×	✓	✓
Koutsopoulos [2013]	Optimal auction-based mechanism including QoS and QoI	✓	✓	×	×
Lee and Hoh [2010a, 2010b]	Reverse auction-based dynamic price (RAPD) mechanism	✓	×	✓	✓
Luo et al. [2014c]	All-pay auction with risk-averse users and strictly individually rational	✓	✓	✓	✓
Wei et al. [2015]	Truthful double auction with dynamic users and providers	✓	✓	✓	✓
Yang et al. [2012]	<i>MSensing</i> reverse auction-based mechanism	✓	✓	×	✓
Yang et al. [2015]	<i>BMT</i> algorithm based on stochastic Lyapunov optimization	✓	✓	✓	✓
Zhao et al. [2014], Zhao et al. [2015]	Two online budget-feasible auction mechanisms	✓	✓	×	✓
Zhang et al. [2015]	Reverse auction for binary task classification under budget constraint	✓	✓	✓	✓
Zhang et al. [2015b]	Truthful incentive mechanisms for crowdsensing	✓	✓	✓	✓
Zhang et al. [2015a]	QoI-aware mechanism for crowdsensing	✓	✓	✓	✓

IR, individual rationality; T, truthfulness; SE, system efficiency; CE, computation efficiency.

Furthermore, one of the ways to ensure truthfulness is to use the second-price *Vickrey-Clarke-Groves* (VCG) auction mechanism [Vickrey 1961]. In a forward auction, the VCG mechanism charges each individual the harm it causes to other bidders in terms of the social welfare utility, whereas in a reverse auction, it pays each user an amount equal to the value contributed by the user to the auction. However, it can be shown that finding the winning set of users in a VCG mechanism is NP-complete. Additionally, a VCG auction is vulnerable to bidder collusion. In particular, if all bidders in a VCG auction reveal their valuations to each other, they can lower some or all of their valuations while preserving who wins the auction.

7.2. Auction-Based Incentive Mechanisms

Much research has been devoted to designing auction-based incentive mechanisms for participatory sensing. Table II summarizes the relevant related work on the topic in alphabetic order of the authors, with a summary of the main contribution. For each work, the set of desirable properties achieved by the proposed auction mechanism is also reported.

The earliest work in this category is that of Lee and Hoh [2010b], which was later extended in Lee and Hoh [2010a]. This work presents the design and evaluation of a simple incentive mechanism called *reverse auction-based dynamic price* (RADP). In such an auction, user u_i tries to sell his sensing data to a service provider by sending his claimed bid prices b_i . The m users having the lowest bid price win the auction and are subsequently rewarded with a payoff proportionate to their claimed bid price. To prevent users who are not rewarded from dropping out of the participatory sensing application, the authors also propose a scheme using the concept of *virtual credit* as a reward for user participation itself. In detail, a user u_i who lost in the previous auction

round $r - 1$ receives virtual participation credit v in current auction round r . Such credit can only be used for decreasing bid price, thus increasing a winning probability of the user for the current auction round. Another important element of RADP is the return on investment (ROI) indicator S_i , which is used as a criterion to determine when a user is dropping out of the system. The ROI index is a function of earned reward over time and the user cost of service. Users evaluate the S_i value every round; if it is below a certain threshold, then they drop out of the system. In addition, RADP includes a rejoinder mechanism, which allows the auctioneer to communicate the maximum winning price ϕ_k to users who churned from the system.

Jaimes et al. [2012] pointed out that the work of Lee and Hoh [2010b] could be improved by considering the location of the users, area coverage, and budget constraints in the proposed auction-based mechanism. Therefore, they propose a novel mechanism called the *greedy incentive algorithm*, which is based on the RAPD mechanism discussed earlier and the *greedy budgeted maximum coverage* (GBMC) algorithm included in Khuller et al. [1999]. In detail, GBMC addresses the coverage problem with budget constraints (which is shown to be NP-hard) by greedily finding a set of users that covers the greatest possible area within a budget constraint.

The problem of guaranteeing a truthful incentive mechanism was explored for the first time in the seminal work of Yang et al. [2012]. In this work, the authors propose a *user-centric* model for participatory sensing in which the PSP announces a set of tasks $\Gamma = \{\tau_1, \tau_2, \dots, \tau_n\}$. Each task τ_j has a value $v_j > 0$ to the PSP. Each user i selects a subset of tasks $\Gamma_i \subseteq \Gamma$ according to preference. Furthermore, based on the selected task set, user i also has an associated cost c_i , which in contrast to Lee and Hoh [2010b] and Jaimes et al. [2012], is *private* and only known to the user. User i then submits the task-bid pair (Γ_i, b_i) to the platform, where b_i is bidding price of user i . Upon receiving the task-bid pairs from all users, the PSP selects a subset \mathcal{S} of users as winners and determines the payment p_i for each winning user i . The utility of user i is $p_i - c_i$, whereas the utility of the PSP is defined as

$$\begin{aligned} u_0 &= v(\mathcal{S}) - \sum_{i \in \mathcal{S}} p_i, \text{ where} \\ v(\mathcal{S}) &= \sum_{\tau_j \in \bigcup_{i \in \mathcal{S}} \Gamma_i} v_j, \end{aligned} \quad (2)$$

which is the sum of value of the tasks executed by the selected users minus the price paid to the users for execution of the sensing tasks. The proposed auction mechanism, called *MSensing*, selects winners and determines payments by following a greedy approach, and therefore it is computation efficient. This, however, makes the auction not system efficient because the user selection and payment is not optimal. The auction is shown to be truthful by using Theorem 1, as well as individually rational. Therefore, four out of five properties are guaranteed by MSensing.

Koutsopoulos [2013] tackles the problem of the truthful incentive mechanism and proposes a mechanism based on an *optimal* reverse auction [Myerson 1981], in which the PSP needs to fulfill a given quality of service (QoS) constraint by “buying” different participation levels from different users. The novelty with respect to Yang et al. [2012] lies in the consideration of QoS constraints, as well as the aspect of QoI of sensing reports in the winner determination phase. In detail, the QoI of sensing reports is modeled by an empirical *quality indicator* q_i continuously updated by the PSP, which essentially measures the relevance or usefulness of information provided by user i in the past. The author claims that this can be quantified by the average deviation of submitted samples from the result of the aggregation of all user samples. On the other hand, QoS is captured by a generic, positive-valued function $g(x)$ of participation-level vector $x = (x_1 \cdots x_n)$, which includes as parameters the vector of qualities of submitted data by users, $q = (q_1, \dots, q_n)$. For example, in applications that consider monitoring of

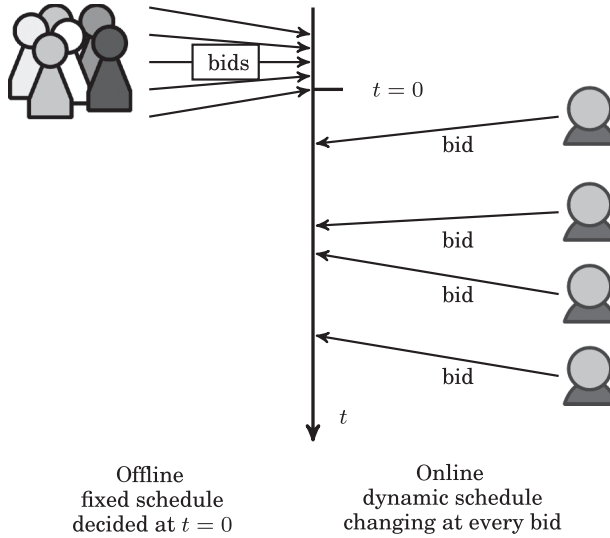


Fig. 7. Offline versus online auction setting in Han et al. [2013].

a quantity of interest, such as air pollution or road traffic condition, $g(\cdot)$ may denote the accuracy of estimation. The target of the mechanism $M(c) = \{x(c), p(c)\}$ is then to compute a winner vector $x(c)$ and a payment level vector $p(c)$, which are a function of the cost vector c , such that its expected expenditure for reimbursing users is minimized. A mechanism is then proposed that guarantees truthfulness and individual rationality.

Luo et al. [2014c] tackle for the first time the problem of providing a truthful mechanism that is also *system efficient*. In particular, previous work had dealt with NP-hard scheduling problems that do not allow optimum revenue for the PSP. In this work, the authors set the prize as a *function* of the winners' contribution to induce the maximum profit, which is defined as the total contribution acquired from all users less the contribution-dependent prize. In addition, they assume that users may be *risk averse*, which means that users may be reluctant to accept a bargain with an uncertain payoff rather than another bargain with a more certain, but possibly lower, expected payoff. They then design an all-pay auction mechanism that maximizes the revenue of the PSP and is *strictly* individually rational for both risk-neutral and weakly risk-averse agents. In other words, such agents can expect a payoff strictly greater than zero and therefore are more incentivized to participate.

Han et al. [2013] studied for the first time the problem of designing truthful incentive mechanisms for participatory sensing in an *online* bidding setting. In particular, in an offline setting, the PSP collects all users' bids before deciding the winners and scheduling the sensing tasks. Conversely, in an online setting, users' bids are revealed one by one, and the PSP must make an irrevocable decision on assigning sensing tasks right at the moment when the user's bid is revealed (Figure 7). Note that this setting is also applicable to a scenario where users arrive at the sensing area at different moments in time. The authors first define the optimum task scheduling problem, which includes for the first time the possible sensing start time s_i and end e_i for each user. After showing the NP-hardness of the problem, they propose two polynomial-time approximation algorithms that approximate the optimum by a value $\mathcal{O}(1)$. Finally, two incentive mechanisms are proposed for the online and offline settings, which are shown to be truthful, individually rational, and computation efficient as they both run in $\mathcal{O}(n^2)$.

Zhao et al. [2014] (extended in Zhao et al. [2015]) further explore the problem of user incentivization in an online auction setting. In particular, the problem here is to select a subset of users before a specified deadline so that the value of services provided by selected users is maximized under the condition that the total payment to these users does not exceed a *budget constraint*. To this end, the authors propose two online incentive mechanisms, called *OMZ* and *OMG*, which guarantee the desired properties of auctions and achieve a competitive ratio⁶ of $\mathcal{O}(1)$ with respect to the offline case. Feng et al. [2014b] also study the problem of online sensing task scheduling as in the work of Han et al. [2013] and Zhao et al. [2014] by also considering *dynamic arrival* of sensing tasks. In particular, they propose two truthful auction mechanisms that take both dynamic smartphones and random arrivals of tasks into consideration. For the offline case, they design an efficient truthful mechanism with an optimal task allocation algorithm of polynomial-time computation complexity $\mathcal{O}(n + \gamma)^3$, where n is the number of smartphones and γ is the number of sensing tasks. For the online case, the authors design a near-optimal truthful mechanism with an online task allocation algorithm that achieves a constant competitive ratio of $\theta(1/2)$. It is also demonstrated that the proposed auction mechanisms achieve truthfulness, individual rationality, and computational efficiency. In another work, Feng et al. [2014a] proposed a different incentive mechanism that takes into account the *location* of smartphone users. Specifically, the tasks here are location based, and users can bid only on tasks that are in the sensing coverage of the smartphone. After proving that optimally determining the winning bids with location awareness is NP-hard, the authors' proposed mechanism consists of a polynomial time and near-optimal task allocation algorithm, as well as a payment scheme that guarantees truthfulness. Differently from Feng et al. [2014b], here the sensing tasks and users' positions are assumed to be known in advance and static.

Gao et al. [2015] consider the sensor selection problem in a general time-dependent and location-aware participatory sensing system, taking the long-term user participation incentive into explicit consideration as in the work of Lee and Hoh [2010b]. To this end, they propose a VCG auction policy for the online sensor selection, which achieves a constant competitive ratio of $\mathcal{O}(1)$ with the optimal offline solution. Yang et al. [2015] develop an adaptive and distribute algorithm OptMPSS to maximize phone user financial rewards accounting for their costs. To incentivize phone users to participate, they propose an algorithm that merges stochastic Lyapunov optimization with mechanism design theory. The authors show that the mechanism achieves an asymptotically optimal gross profit for all phone users.

For the first time, Zhang et al. [2015a] designed schemes to tackle the problem of malicious users in crowdsensing. They first designed a mechanism called *EFF* that eliminates dishonest behavior with the help of a TTP. Then, another mechanism called *DFE* was designed that discourages dishonest behavior without the help from any third party. They prove that DFE is semitruthful, which discourages dishonest behavior such as free-riding and false reporting when the rest of the individuals are honest while guaranteeing transaction-wise budget balance and computational efficiency.

7.2.1. Discussion. Despite the merit of being the first auction-based mechanisms proposed for participatory sensing systems, Lee and Hoh [2010b] and Jaimes et al. [2012] do not guarantee all four properties of auctions. In particular, these approaches do not consider that cost information is private and that users may misrepresent their real costs to maximize their own payoffs. As a result, the schemes are not truthful. Given that GIA and the RAPD algorithm determine the winners of the auction in polynomial

⁶A mechanism is $\mathcal{O}(g(n))$ -competitive if the ratio between the online solution and the optimal solution is $\mathcal{O}(g(n))$.

time and guarantee nonnegative utility, the mechanisms are system efficient and individually rational. Differently from Lee and Hoh [2010b] and James et al. [2012] do not select the users in an optimum way due to the hardness of the coverage problem, and therefore it is not system efficient.

Although the work of Koutsopoulos [2013] provides the only attempt to formalize information quality as part of the incentive mechanisms, the formulation of QoS and QoI does not take into account the actual complexity of determining the quality of each sensing report. Indeed, no algorithm is proposed to accomplish such a goal. The authors also fail to calculate the complexity of the optimization problem defined in the work, nor are algorithms formalized to solve the optimization. Therefore, the system and computational efficiency of the mechanism are not guaranteed. Furthermore, the main weakness of Yang et al. [2012], Feng et al. [2014a], and Gao et al. [2015] lies in the assumption of static tasks and users. Although the mathematical analysis in these works is sound, such an assumption makes the approaches unrealistic for practical applications.

Similarly to non-auction-based mechanisms, the limitations of existing work in designing an auction-based mechanism is the assumption of perfect rationality of participants. Furthermore, a large-scale validation of auction-based mechanisms is still missing, which is needed to understand whether auction-based mechanisms can work in real-world implementations.

7.3. Preliminaries on Game Theory

Game theory is “the study of mathematical models of conflict and cooperation between intelligent rational decision-makers” [Myerson 1991]. Originally developed to model problems in the field of economics, game theory has recently been applied to a variety of problems, in most cases to solve the resource allocation problems in competitive environments [Hassan et al. 2012; Birje et al. 2014], including the design of incentive mechanisms for participatory sensing systems. This is because the entities involved (i.e., the participating users) are autonomous agents, making decisions only for their own interests. To this end, game theory provides sufficient theoretical tools to analyze users’ behaviors and actions.

7.3.1. General Concepts. Game theory models scenarios where individual decision makers have to choose specific actions that have mutual or possibly conflicting consequences. A game consists of three major components:

- Players:** Players are the entities involved in the decision-making process and are denoted by a finite set $\mathcal{N} = \{1, 2, \dots, n\}$.
- Strategies:** Each player can choose a strategy s_i in the set S_i of possible strategies. A strategy profile s is a vector containing all of the strategies (i.e., $s = (s_1, s_2, \dots, s_n)$). Obviously, we have $s \in S = \otimes_{i \in \mathcal{N}} S_i$, where \otimes is the Cartesian product.
- Utility or payoff:** The utility $u_i : S \rightarrow \mathbb{R}$ of player i is a measurement function on the possible outcome determined by the strategies of all players, where \mathbb{R} is the set of real numbers.

Players are usually assumed to be rational and selfish, which means that each player is only interested in maximizing his own utility without respecting others’ and the system’s performance [Tadelis 2013]. Let s_{-i} denote any strategy profile excluding s_i , and let $s = (s_i, s_{-i})$ for simplicity. We say that player i prefers s_i to s'_i if $u_i(s_i, s_{-i}) > u_i(s'_i, s_{-i})$. When other players’ strategies are fixed, player i can select a strategy, denoted by $b_i(s_{-i})$, which maximizes its utility function. Such a strategy is called a *best response* of player i . A strategy of player i is *dominant* if, regardless of what other players do, the strategy earns player i a larger utility than any other strategy. To study the

		Participant B	
		Low Price	High Price
Participant A	Low Price	2 3	5 6
	High Price	3 4	2 8

Fig. 8. An example of Stackelberg equilibrium.

interactions among players, the concept of *Nash equilibrium* (NE) is introduced. A strategy profile constitutes an NE if none of the players can improve his utility by unilaterally deviating from his current strategy.

Definition 1. A strategy profile s^* is a Nash equilibrium if

$$u_i(s^*) \geq u_i(s_{-i}^*, s'_i) \quad \forall i, \forall s'_i \in S_i.$$

Games can be classified into two categories: *strategic* or *extensive* form game. The strategic form game is played only once. In this game, the players make their decisions simultaneously without knowing what others will do. On the contrary, the extensive form game represents the structure of interactions between players and defines possible orders of moves in different games. The *repeated* game is a class of the extensive form game, in which the strategic game is repeated every time. At the beginning of each stage, players observe the past history of strategies before making decisions. The number of stages may be finite or infinite. The utility of each player is the accumulated or discounted utility through all stages. Therefore, players care not only about the current utility but also the future utilities.

7.3.2. Stackelberg Games. A Stackelberg game is an extensive form game used to model the competition between one player, called the *leader*, and a set of players, called the *followers*. In this game, the leader takes action first and then the followers take actions. The leader knows *ex ante* that the followers observe his action and take actions accordingly. The NE in the Stackelberg game is called *Stackelberg equilibrium* (SE).

Figure 8 depicts the payoff matrix of a Stackelberg game between two competing law firms as example. We assume that Participant A is the leader and Participant B is the follower. The actions for both A and B are low price (LP) and high price (HP). If A plays strategy LP, B would play strategy HP, as it gives player B a utility of 5 (as opposed to a utility of 2 should B play strategy LP). This leads to a utility of 6 for A. If A plays strategy HP, B would play strategy LP, as it gives B a utility of 3 (as opposed to a utility of 2 should B play strategy HP). This leads to a utility of 4 for A. Hence, A would play strategy LP, as doing so would result in a utility of 6 compared to 4 by playing strategy HP. As explained before, B would play HP if A plays LP. Therefore, the SE of this game is (LP, HP).

The *existence* of an SE is important, as an SE strategy profile is *stable* (no player has an incentive to make a unilateral change), whereas a non-NE strategy profile is unstable. In addition, the *uniqueness* of an SE allows the leader to predict the behaviors of the followers and thus enables the leader to select the optimal strategy for himself.

		<i>Behavior</i>	
		<i>Honest</i>	<i>Dishonest</i>
<i>Parking</i>			
Successful	$D + pX$	R	
Unsuccessful	R	D	

Fig. 9. Payoff matrix for consumers: Parking versus Behavior.

7.4. Non–Auction-Based Incentive Mechanisms

Very few incentive mechanisms involving non–auction-based game theory have been proposed. Hoh et al. [2012] considered the problem of trustworthy crowdsourced parking and presented an incentive platform named *TruCentive*. The target of such a platform is twofold: (1) it provides incentives to stimulate the contribution of high-quality parking information, and (2) it prevents malicious participants from spamming the parking service with a high volume of useless data. The first aim is achieved by a simple yet effective protocol in which contributors and consumers “trade” parking information. In detail,

- A contributor submits a message to TruCentive, receiving in turn a reward of D units.
- A consumer “buys” a message for available parking spot information, depositing N units.
- The consumer drives to the parking spot and sends back an active confirmation of whether the parking spot information led to her successfully parking in a reserved space or not. If the confirmation is unsuccessful, R credits are refunded to the consumer. If successful, X bonus points are credited to the contributor.

The second target is achieved by introducing a game-theoretical–formulated incentive protocol. The key idea behind the approach is that consumers who successfully park at a traded spot can resell that spot through TruCentive if they tell the truth. In particular, if consumers lie about the success status of their prior parking, they cannot resell this parking spot to the next consumer. Therefore, reward parameters are set to ensure that the average gain of reselling is higher than the gain by lying and receiving a refund. Figure 9 depicts the payoff matrix for consumers as a function of the behavior (honest or dishonest) and prior parking status (successful or unsuccessful). To have (Successful, Honest) and (Unsuccessful, Honest) best strategies, $D + pX \geq R \geq D$ must hold, which means that $X \geq \frac{1}{p}(R - D)$. This provides a lower bound for the bonus X . Regarding the upper bound, the authors argue that the payment strategy must be profitable for the administration of the system, and therefore the choice of X must take into account total revenue and costs of providing the service.

Duan et al. introduced [Duan et al. 2012] and extended Duan et al. [2014] an analysis of different incentive mechanisms to motivate the collaboration of smartphone users on data acquisition and distributed computing applications. To collect massive amounts of sensitive data from users, they propose a game-theoretical reward mechanism based on a Stackelberg game, where the PSP can earn a fixed positive revenue only if enough smartphone users agree to participate. The authors argue that this model is sound, as

an incentive mechanism is effective only when it is possible to build a large enough database to support the sensing application (e.g., live traffic maps).

Specifically, the game model proposed is a two-stage Stackelberg game under incomplete information. In the first stage, the master announces the total reward R to be allocated among the required minimum number n_0 of participating users. For the master to receive revenue V , the number of participating users n must be greater or equal to n_0 . In the second stage, each user decides whether to join the collaboration or not by predicting other users' costs and decisions, along with the expected reward. Interestingly enough, the cost C_i for user u_i is modeled as a function of both privacy loss and energy consumption. In the analysis, it turns out that it is better to reward users' participation efforts irrespective of the result of the collaboration. This encourages users to collaborate and hence increases the chance of collaboration success. Then, the target of the authors is to characterize the subgame perfect equilibria (SPE) that specify players' stable choices in all stages. As expected, the results indicate that if the master knows the users' collaboration costs C_i , then the selection is optimum, as it can involve only users with the lowest costs.

The most important contribution pertaining to this class of incentive mechanisms was introduced by Yang et al. [2012]. In their landmark work, they consider two system models: the *platform-centric model*, where the PSP provides reward shared by participating users, and the *user-centric model*, where users have more control over the payment that they will receive. For the platform-centric model, Yang et al. designed an incentive mechanism using a Stackelberg game, where the PSP is the leader and the users are the followers.

It is worthwhile to describe this method in detail due to its remarkable theoretical properties. In such a model, there is only one sensing task, and the PSP announces a total reward $R > 0$ to incentivize users' participation to it. The sensing plan of user u_i is denoted by t_i and represents the time units u_i is willing to provide to accomplish the sensing service, whereas c_i includes the sensing cost for user u_i . By defining as \mathcal{U} the set of all users, the utility \bar{u}_i of the user u_i is defined as

$$\bar{u}_i = \frac{t_i}{\sum_{j \in \mathcal{U}} t_j} \cdot R - t_i \cdot c_i, \quad (3)$$

which ultimately is reward minus cost. The utility of the PSP is defined as

$$\bar{u}_0 = \lambda \log \left(1 + \sum_{i \in \mathcal{U}} \log(1 + t_i) \right) - R, \quad (4)$$

where $\lambda > 1$ is a system parameter, and the inner and outer log terms quantify, respectively, the value obtained from the sensing time of user i and the overall participating users. The target of the PSP is to decide the optimal value of R so as to maximize Equation (4), whereas each user decides its sensing time t_i to maximize Equation (3) for the given value of R . This problem is modeled as a Stackelberg game, where the PSP is the leader and the participants are the followers. It is demonstrated that a unique SE exists, and it also shown how to compute such an SE. This is an important result, as the utility of the PSP is maximized, and none of the users can improve his utility by unilaterally deviating from his current strategy—hence, the strategy is stable.

7.4.1. Discussions. The major limitation of the work in this category is the assumption of *perfect rationality* of participants and the absence of *malicious participants*. In other words, the calculation of the equilibria holds only whether the participants willingly choose to perform the action that is supposed to be best for them. However, do they *know* the action that is best for them? Are they willing to do it *regardless* of other factors

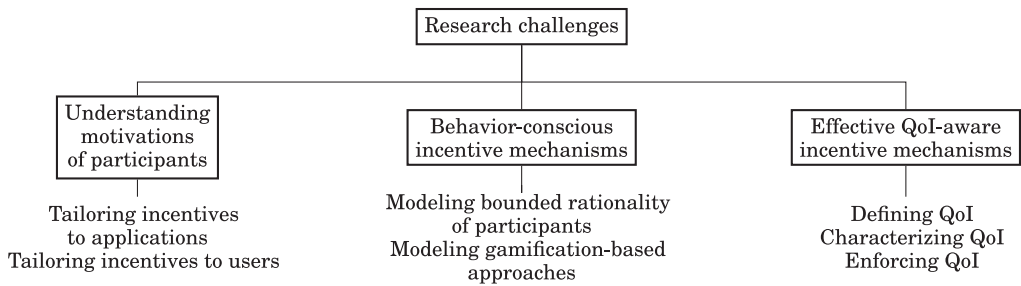


Fig. 10. Summary of proposed research challenges.

that may influence their choice (e.g., time available to perform sensing services)? How does the system perform when participants *willingly* become malicious, even it is not the most rational choice for them? These questions are not addressed by current approaches, which allow for comprehensive mathematical analysis by relying on strong assumptions that, in reality, may not hold.

Regarding such limitations, the performance of the TruCentive solution [Hoh et al. 2012] depends on a good choice of parameter X , which represents the bonus points that are credited for a successful and honest contribution. However, the authors did not propose any methodology to estimate or set X as a function of other system parameters, which limits the system’s applicability in real-world applications. The two-stage Stackelberg game approach introduced by Duan et al. [2012] assumes that the optimum strategy is found by knowing the collaboration costs of all users, which is unrealistic in practical scenarios, as users may (perhaps maliciously) provide incorrect information about their costs. An even stronger assumption is applied in the platform-centric Stackelberg game introduced by Yang et al. [2012], which assumes that costs and sensing times are perfectly known by the PSP.

8. OPEN RESEARCH CHALLENGES

There has been an increasing emergence of research devoted to designing incentivization mechanisms for participatory sensing systems. Although a significant number of solutions applicable to multiple contexts have been proposed, there are still several research challenges to be tackled to allow the widespread use of effective incentive mechanisms in participatory sensing. Figure 10 summarizes the proposed research agenda to improve and transform existing incentive mechanisms.

8.1. What is the Best Way to Incentivize Users?

Before developing an incentive mechanism, a fundamental question must be answered: what incentive works *best* to motivate volunteers to contribute to a participatory sensing campaign? In the context of participatory sensing, the best way to incentivize users remains unknown. More specifically, although recent research has tried to understand the relation between demographics and user participation [Christin et al. 2013a; Omokaro and Payton 2014], there is lack of a general, empirical study on the motivations of volunteers to perform participatory sensing tasks and the effectiveness of participatory sensing incentives across different contexts. Furthermore, to date, incentives for participatory sensing have largely been applied in an ad hoc, “one size fits all” manner, assuming that all applications have the same requirements and people have all the same needs. Additional study is needed to develop a systematic approach to the design and selection of incentives that are *tailored* to a particular application

and *personalized* to motivate individual volunteers to perform participatory sensing tasks.

8.1.1. Tailoring Incentives to Applications. Recent work on participatory sensing has posited that the characteristics of applications, particularly with respect to the kinds of sensing tasks required, can impact the effectiveness of incentives [Rula et al. 2014]. In particular, sensing tasks may be implicit, occurring in the background with little or no user interaction (e.g., capturing location traces over the course of a predetermined time period), or may require explicit user intervention (e.g., capturing a report of the perceived conditions at a local watershed). Some sensing tasks have spatiotemporal constraints, requiring a volunteer to be at a particular location at a particular time. Sensing tasks also differ in terms of the cognitive overhead required; some sensing tasks simply require the capture of a sample from sensors on a mobile device, whereas others require volunteers to provide observations, interpretations, or opinions. Experimental research with large-scale deployments of participatory sensing applications can lead to a better understanding of how incentives can be tailored to the required sensing task. More broadly, the purpose of the participatory application itself may appeal to a potential volunteer's intrinsic motivation and impact participation. Studies in the related domains of citizen science and crowdsourcing show that intrinsic motivators often have a greater impact than remunerative rewards on increasing the quality of task performance [Nov et al. 2011; Rogstadius et al. 2011; Kaufmann et al. 2011]. In fact, offering an incentive that appeals as an extrinsic motivator may have a negative impact on an individual's intrinsic motivation and can therefore result in reducing the overall motivation to perform a task [Gneezy and Rustichini 2000]. Understanding what motivates individuals, through the use of surveys and interviews, can aid in tailoring participatory sensing incentives that are effective in garnering participation.

8.1.2. Tailoring Incentives to Users. Research that explores motivation in the context of volunteerism has shown that several factors influence the motivations of an individual, including age [Carstensen et al. 1999; Wilson 2000; Okun and Schultz 2003], race [Musick et al. 2000; Morrow-Howell et al. 1990], class [Musick et al. 2000], religion [Musick et al. 2000], gender [Eisenberg 1992; Wilson and Musick 1997; Wuthnow 1995; Raddick et al. 2009], and education [Rosenthal et al. 2010]. This suggests that there is an opportunity for *personalized* incentives that appeal to the motivations of an individual.

Researchers are beginning to explore this idea within the context of participatory sensing. Work by Omokaro and Payton [2014] takes a first step toward exploring how demographics affect the motivations of potential participatory sensing volunteers. Preliminary results from a survey of more than 200 people indicate that individuals from different age groups respond similarly to incentives intended to appeal to extrinsic motivations but display significant differences in their response to incentives intended to appeal to intrinsic motivations. Another study was conducted by Christin et al. [2013a], who analyze the impact of demographics, incentives, and gathering conditions on both the importance and value of privacy by means of a questionnaire-based user study with 200 anonymous participants.

Although these preliminary findings show promise for this direction of research, other factors that impact an individual's motivation to contribute to participatory sensing campaigns remain to be explored. In particular, the sensing process takes time, interrupts other activities, and consumes additional battery power and data traffic bandwidth. How do these issues impact the users' willingness to participate? What is the right amount of incentive, and how much can we ask from a particular user in terms of privacy loss, time, energy, and bandwidth resources? Further quantitative and qualitative study through the use of surveys, interviews, and participatory

sensing deployments with large and diverse user populations is needed to understand the motivations of volunteers and the effectiveness of incentives to appeal to those motivations within the unique context of participatory sensing. Research efforts should also consider the life cycle of motivation; an individual's motivation to contribute to a participatory sensing campaign may change over time, as has been found to be the case in citizen science projects [Rotman et al. 2012].

8.2. Toward Behavior-Conscious Incentive Mechanisms

So far, game-theoretical-based incentive mechanisms have always implicitly assumed the users are *perfectly rational*, which means always taking the choice that maximizes their utility. However, what happens when users behave in a way that is *less than rational*? Practical experience suggests that the assumption of perfect rationality hardly holds in reality, as human beings are driven and influenced by different motivations, such as emotional or personal constraints [Pita et al. 2010], or simply because remunerative incentives are not effective. Therefore, even individuals who intend to make rational choices are often bound to make *satisfying* or *necessary* (rather than maximizing or optimizing) choices in complex situations. For these reasons, the incentive mechanisms proposed present a significant gap between the theoretical modeling and the *actual* behavior of users in participatory sensing contexts. To tackle such a challenge, one possible solution may be modeling interactions by using concepts from *behavioral game theory* (BGT) [Camerer 2003a]. BGT uses experimental evidence to inform mathematical models of cognitive limits, learning rules, and social utility of choices [Camerer 2003b]. It primarily has three components: (1) mathematical theories of how moral obligation and vengeance affect the way people bargain and trust each other, (2) a theory of how limits in the brain constrain the number of steps of reasoning that people naturally do, and (3) a theory of how people learn from experience to make better strategic decisions.

8.2.1. Modeling Bounded Rationality of Participants. Among others, one of the powerful tools that BGT offers is the concept of *bounded rationality* [Simon 1957, 1982]. The concept stems from the fact that in general, humans make decisions under three unavoidable constraints: (1) only limited, often unreliable, information is available regarding possible alternatives and their consequences; (2) the human mind has only limited capacity to evaluate and process the information that is available; and (3) only a limited amount of time is available to make a decision. One of the approaches [Rubinstein 1998] to model bounded-rationality behaviors is to directly and explicitly involve *procedural* aspects of decision making in the model. A procedural aspect is defined in this context as the *rationale* that leads the decision maker to a particular behavior, which might be different from the expected one (i.e., the one that maximizes the user's utility). Some examples, cast in the context of participatory sensing, are as follows:

- Users may be concerned about the *complexity* of the strategy that they employ. For example, choosing the simpler strategy instead of the optimum one might be better for some users, as demonstrated in Kahneman and Tversky [1979].
- Users might have limited ability to *understand* the game, such as from having incomplete information at their disposal. The information may also be *asymmetrical*, which means that some users know more than others about the game being played.
- Users may be *time constrained* and may not be able (or willing) to play the optimum strategy according to the game being played. For example, if the interaction between the user and the PSP is repeated, the PSP might play an equilibrium according to a model based on an extensive form game. However, the equilibrium played by the users may be calculated by considering a different time horizon and therefore mismatch the ones calculated by the PSP.

—In realistic contexts, participating users might not know the details of the game been played. Therefore, they need to *learn* over time the strategy that maximizes the payoff. In such a context, users might have different *learning strategies*. For example, some might use a reinforcement approach [Barto 1998] (i.e., adapting the strategy as a function of current and past payoffs), whereas others might use anticipatory learning [Camerer et al. 2002] to reason more thoughtfully on what the other players are doing and the game being played.

Therefore, it becomes necessary to embed these and other procedural aspects while modeling incentive mechanisms. We need to identify restrictions on the space of preferences that are compatible with those procedures and then optimize based on those restrictions. One way to incorporate procedural aspects, and therefore uncertainty in the equilibria that will be played by users, is to study the *quantal response equilibria* (QRE) of the game, a concept first proposed by McKelvey and Palfrey [1995]. QRE provide a statistical framework to analyze games that incorporate realistic limitations to rational choice modeling of games. In particular, QRE allow every strategy to be played with nonzero probability, and so any strategy is possible (although not necessarily reasonable). By far, the most common specification for QRE is the *logit* equilibrium (LQRE) [McKelvey and Palfrey 1995], where a player’s strategies are chosen according to the probability distribution

$$\mathbb{P}\{a_i\} = \frac{\exp\{\lambda \cdot \sum_{a_{-i} \in A_{-i}} \mathbb{P}\{a_{-i}\} \cdot u_i(a_i, a_{-i})\}}{\sum_{a'_i \in A_i} \exp\{\lambda \cdot \sum_{a_{-i} \in A_{-i}} \mathbb{P}\{a_{-i}\} \cdot u_i(a'_i, a_{-i})\}}. \quad (5)$$

The λ parameter is defined as the “rationality” parameter: the choice of action becomes purely random as $\lambda \rightarrow 0$, whereas the action with the higher expected payoff is chosen as $\lambda \rightarrow \infty$. Analogously to Nash equilibria, QRE can be calculated for normal form games [McKelvey and Palfrey 1995] and extensive form games [McKelvey and Palfrey 1998]. Recent advances in the field have shown that the computation of QRE can be done by maximum likelihood estimation of the model’s parameters [Choi et al. 2012] or by techniques such as the homotopy method [Rong et al. 2015], which takes polynomial time. The value of λ is usually chosen according to experimental data; however, such data does not yet exist to formulate QRE for games in the context of participatory sensing.

Additional research is therefore needed to model the λ parameter and therefore obtain more realistic equilibria. Although it is true in general that irrationality might depend on the participatory sensing application being considered, we believe that large-scale data collection campaigns with a sufficient number of participants could help solve this issue.

8.2.2. Modeling Gamification-Based Approaches. As we discussed in Section 6, gamification [Deterding et al. 2011] has been proposed as a viable and effective technique to incentivize users’ participation using a natural (i.e., based on joy or entertainment) incentive type instead of a remunerative one. Although some gamification-based incentive mechanisms have already been proposed [Kawajiri et al. 2014; Mukherjee et al. 2014; Ueyama et al. 2014], it is still to be demonstrated through large-scale deployments whether these mechanisms may work effectively in the context of participatory sensing. In particular, on one hand, the leaderboard-based system used by Furchgott [2010] has proven to be effective in keeping users in the sensing loop. However, on the other hand, recent studies [Hamari et al. 2014] cast doubts on gamification, as the authors argue that gamification effects greatly depend on the context in which gamification is being implemented, as well as on the users using it. Therefore, additional experimental research is needed to understand and validate the conditions by which

gamification is a good strategy for user incentivization in participatory sensing and, possibly, generalize the concept to a common framework that can be used by participatory sensing systems. Indeed, by far, existing gamification-based mechanisms have essentially been based on heuristics and do not provide a framework to analyze and model the behavior of users in participatory sensing under gamification-based incentives. Although some modeling languages have been proposed [Herzig et al. 2013], they are general purpose and lacking the ability to capture the complex interactions in participatory sensing. Therefore, research effort has to be put forth to identify positive and negative aspects of the approach as a function of the specific participatory sensing being considered.

8.3. Toward Effective QoI-Aware Incentive Mechanisms

One of the greatest limitations of existing incentive mechanisms, and more generally of participatory sensing systems, is that they are not effective in tackling the problem of verifying the actual QoI of sensing reports. In particular, the research efforts to solve such challenge can be divided in two main categories:

- Reputation-based frameworks*: These frameworks use concepts such as information provenance (i.e., location of users) [Wang et al. 2011, 2013] or consensus-based techniques [Huang et al. 2010] to determine the reliability of users and therefore filter out unreliable reports from the systems. The main issue of reputation-based systems is that they are prone to collusion-based attacks or the location-spoofing-based attacks described in Section 5.1. Therefore, such frameworks cannot be directly used in real-world participatory sensing systems.
- QoI-aware incentive mechanisms*: Some incentive mechanisms, such as those of Koutsopoulos [2011, 2013], reward the participating users based on the perceived QoI of sensing reports. Usually, the QoI of sensing reports is calculated using heuristic functions [Tham and Luo 2013] and do not measure the actual quality of the sensing report as compared to the real-world quantity being measured.

To the best of our knowledge, the only work that addresses at once collusion- and location-based attacks is that of Restuccia and Das [2014], by proposing a methodology based on MSAs (see Section 6) that validates and improves the QoI of sensing reports in a realistic, scalable, and secure way. However, one of the limitations of the work of Restuccia and Das [2014] is that they do not provide a detailed definition of QoI, nor do they address the problem of *how* to determine the QoI of sensing reports. More specifically, they assume that QoI can be computed by using external functions tailored to such a purpose. However, this might not be the case when *multimedia* data (e.g., audio/video feed, pictures) is being collected by the participatory sensing system.

In particular, when the data is coming from physical sensors such as temperature, pressure, or light, the QoI may be defined as the accuracy of that measurement with respect to the real phenomenon being monitored. However, how do we define the QoI of a picture, of a sound, of a video? In such a case, the specific context of the participatory sensing application may significantly influence the definition of QoI. For example, in the case of noise pollution monitoring [D'Hondt et al. 2013], the maximum noise level in decibels might be sufficient to characterize QoI. On the other hand, in the case of voice recognition [Lu et al. 2011] and/or applications that count the number of speakers in a room [Xu et al. 2014], precise audio measurements (in terms of portion of spectrum detected) could be needed to recognize the person and/or how many people are currently in that room. Therefore, additional research is necessary to provide different definitions of QoI that are valid for the spectrum of participatory sensing systems available today.

Furthermore, although the approach based on MSAs [Restuccia and Das 2014] is very promising, it is still necessary to model, and possibly optimize, the QoI as a function

of the resources (e.g., MSAs) employed. In particular, can we design a mechanism to know in advance how many resources are needed to guarantee a certain QoI of the accepted sensing reports? Can we predict the probability of accepting an unreliable sensing report and reduce it as a function of the resources employed? Addressing these issues is extremely challenging, given the hardly predictable behavior of participants.

9. CONCLUSIONS

Smart devices have revolutionized our lives and the way we interact with the surrounding environment. What was technologically a dream 20 years ago has now become reality, and with more and more users embedding pervasive technologies in their daily lives, an immense number of novel applications that drastically improve people's everyday life are now possible. Among all, participatory sensing is certainly one of the most promising paradigms, as it allows one to dramatically decrease infrastructure costs and obtain detailed information about the phenomenon being monitored.

In this article, we have characterized the state of the art of incentive mechanisms in participatory sensing systems and have proposed a set of open research challenges related to the topic. First, we provided an overview of participatory sensing and identified the main components of existing incentive mechanisms. Then, we presented a taxonomy of such mechanisms, based on their purpose and their methodology, and discussed important contributions, insights, and limitations of the state of the art within each category of the taxonomy. Finally, we proposed and discussed a set of research challenges in incentivizing users in participatory sensing, which comprise guaranteeing QoI, modeling the behavior of users, and understanding the best reward strategy.

Future work will be dedicated to investigating the proposed research challenges. In particular, we plan to build a large-scale deployment of a participatory sensing system on our campus and study the impact of various incentive types, both intrinsic and extrinsic, on the frequency and quality of sensing reports by participants. We also plan to design incentive mechanisms that assume bounded user rationality and test them on practical test beds.

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Received April 2015; revised January 2016; accepted January 2016