RC25086 (C1012-015) December 13, 2010
Computer Science

IBM Research Report

Efficient Network Management for Context-Aware Participatory Sensing

Chi Harold Liu[1], Pan Hui[2], Joel W. Branch[3], Chatschik Bisdikian[3], Bo Yang[1]

[1]IBM Research Division
China Research Laboratory
Building 19, Zhouguancun Software Park
8 Dongbeiwang West Road, Haidian District
Beijing, 100193
P.R.China

[2]Deutsche Telekom Laboratories/TU-Berlin
Berlin, Germany

[3]IBM Research Division
Thomas J. Watson Research Center
P.O. Box 704
Yorktown Heights, NY 10598

Efficient Network Management for Context-Aware Participatory Sensing

Chi Harold Liu[†], Pan Hui[§], Joel W. Branch[‡], Chatschik Bisdikian[‡] and Bo Yang[†]

[†]IBM Research - China, Beijing, China

[§]Deutsche Telekom Laboratories/TU-Berlin, Berlin, Germany

[‡]IBM T. J. Watson Research Center, Hawthorne, U.S.A.

[†]{chiliu, boyang}@cn.ibm.com, [§]pan.hui@telekom.de, [‡]{branchj, bisdik}@us.ibm.com

***Abstract*—Participatory sensing is becoming more popular with the help of sensor-embedded smartphones to retrieve context-aware information for users. However, new challenges arise for the maintenance of the energy supply, the support of the quality-of-information (QoI) requirements, and the generation of maximum revenue for network operator, but with sparsely research exposure. This paper proposes a novel efficient network management framework to tackle the above challenges, where four key design elements are introduced. First is the *QoI satisfaction index*, where the QoI benefit the queries receive is quantified in relation to the level they require. Second is the *credit satisfaction index*, where the *credits* are used by the network operator to motivate the user participation, and this index is to quantify its degree of satisfaction. Third is the Gur Game-based distributed energy control, where the above two indexes are used as inputs to the mathematical framework of the Gur Game for distributed decision-making. Fourth is the dynamic pricing scheme, based on a constrained optimization problem to allocate credits to the participants while minimizing the necessary adaptation of the pricing scheme from the network operator. We finally evaluate the proposed scheme under an event occurrence detection scenario, where the proposed scheme successfully guarantees less than 7% detection outage, saves 80% of the energy reserve if compared with the lower bound solution, and achieves the suboptimum with only 4% gap if compared with optimal solution.**

I. Introduction

The past several years have seen the astounding proliferation of affordable, wireless, and easily programmable mobile computing and communication devices such as smartphones and now, tablet computers. While integrated media and location-tracking features (e.g., cameras, GPS receivers, accelerometers, etc.) have become standard fare, one can expect a rapid increase of other "sentient" functions via additional integrated or peripheral environmental sensors; examples include sensors for measuring pollen, air-pollutants, humidity, etc. Overall, these advancements are bringing forth the "participatory sensing" model, in which participants use personal mobile computing devices to collect, possibly analyze, and make available nearby environmental data for large-scale applications. Notable examples include using smartphones to monitor road and traffic conditions [1], [2] and locate habitat-destroying plants and animals [3].

This work is partly funded by the Thin Sense Project of Deutsche Telekom Laboratories. Initial work was performed through participation in the International Technology Alliance sponsored by the U.S. Army Research Laboratory and the U.K. Ministry of Defence. Parts of this paper are also under consideration for a 6-page workshop paper at IEEE IQ2S 2011. This paper largely extends previous contributions quite distinctly focusing on the participatory sensing with the novel system architecture, credit estimation and allocation, and its involvement into the distributed decision making process, with extensive simulation results.

Our work is motivated by the application scenario shown in Fig. 1, which is also derived from the smartphone-based micro-blogging system described in [4]. Fig. 1 shows a population of mobile device users subscribing to a wireless service provider (or *network operator*) and a user (or *querier*) of a participatory sensing application offered by the network operator. The querier asks the application for some information about a landmark, such as the size and location of crowds near a tourist site. The application then forwards the query to the mobile device users near the site. Upon receiving the query, mobile device users decide whether they will respond and send data back to the application, where data processing may occur before a result is returned to the querier. The users who supplied data would receive some form of credit from the service provider as a reward for supporting the efficacy of the application.

Supporting application scenarios such as the one above requires addressing the following challenge: *balancing the quality of information produced by the system with its energy-efficiency, while providing satisfactory benefits to the querier, network operator, and participants*. Quality of information (QoI) represents a (set of) metric(s) to judge if information is *fit-for-use* for a particular purpose [5], [6]. For example, the QoI of the "crowd identification" response above may include factors such as latency, proximity, and accuracy, the last of which may be a factor of the quality of photos taken at the site. Unfortunately, increasing QoI generally increases the energy usage of mobile devices collecting the data. For example, a high quality response in the scenarios above would most likely require video from a plurality of devices, not just one.

While the problem above also exists for traditional sensor networks, it is compounded in the participatory sensing context for multiple reasons. First, as opposed to traditional sensor "motes," smartphones (and the like) are not dedicated sensor devices and have competing *traditional* demands for energy resources (e.g., voice calls, text messages, and gaming). Second, smartphones are *personal* devices upon which any outside party cannot expect to impose traditional sensor network energy management mechanisms such as duty cycling and power

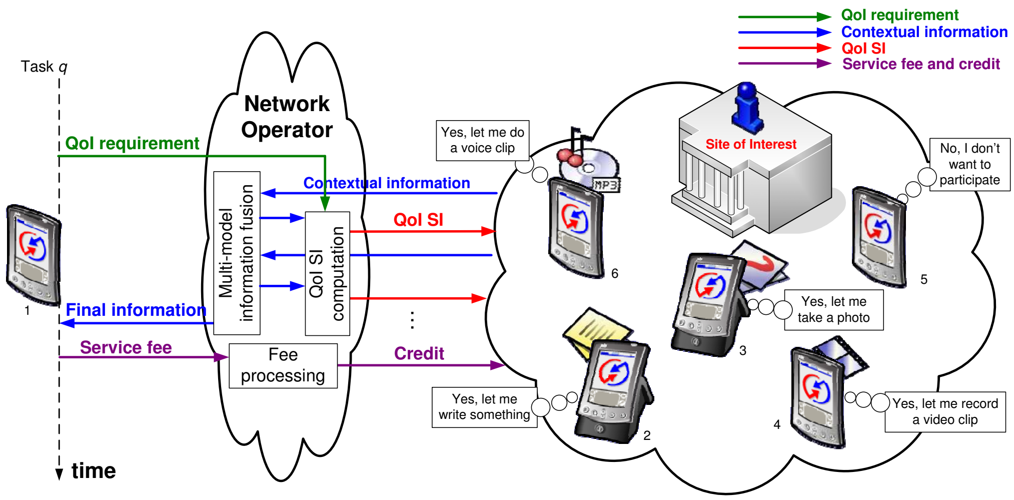

Fig. 1. The considered participatory sensing scenario, where smartphone 1's user request for contextual information of interest is directed to a set of users labeled as 2-6 within the proximity. Some users decide to participate via contributing certain type of contextual information, for example, text message, voice clip, image, and video, while others may decide not to participate.

state control; only the device's user can control energy usage. However, as described in the earlier application scenario, incentive-based techniques may be used to influence energy usage on personal devices and furthermore, help balance QoI and energy-efficiency. These challenges and general approach serve as the basis for our work.

This paper proposes a novel QoI-aware energy-efficient network management framework for participatory sensing. Our solution approaches the problem from two angles, the first being that of the network operator. Here, the goal is to maximize the QoI of the system by maximizing the participation of mobile device users, while minimizing the cost of doing so, via minimizing the credits granted for participation. We model this as a constrained optimization problem and quantify the QoI benefit that queriers receive in relation to the level of QoI they request as the *QoI satisfaction index*. The second angle of our approach relates to the mobile device user. Here, we propose a distributed scheme for deciding both the device's energy consumption state and the quality of data to contribute to the application. For this, we employ the mathematical framework of the Gur Game [7], [8], where notions of reward and punishment, represented by credits and energy loss respectively, locally guide the balance between QoI and energy-efficiency.

The rest of the paper is organized as follows. In Section II, we highlight related research activities. Section III establishes a formal model of our system. Section IV and Section V describe the QoI satisfaction index and credit expectation index. Section VI introduces the overall network management framework, followed by the Gur Game based distributed energy management scheme in Section VII. Finally, Section IX concludes the paper and presents the future work.

II. Related Work

Recently, there are a number of emerging applications for smartphone sensing. Sensor-equipped vehicles are used to detect and report the surface conditions of roads [1], [2]. "E-SmallTalker" was presented in [9] to facilitate the stranger social networking. EnTracked [10], based on the estimation and prediction of system conditions and mobility, schedules position updates to track pedestrian targets equipped with GPS-enabled devices. The economic model of user participation incentive was studied in [11], by proposing reverse auction dynamic price with virtual participation credit mechanism where users can sell their sensing data to a service provider. Our work is largely motivated by "Micro-Blog" in [4], allowing smartphone-equipped users to generate and share geo-tagged multimedia. However, different from [4], we aim at addressing challenges related to system management experienced by network operators and smartphone users. Our goal is to explore the mathematical framework of managing the energy reserve in a distributed way while providing satisfactory levels of QoI and maximum revenue for the network operators simultaneously.

Regarding the energy-aware sensor network platforms, network-wide solutions like Lance [12] require centralized control. For distributed solutions, EEMSS in [13] presented a sensor management scheme that selectively turns on the minimum set of sensors to monitor user state and triggers a new set of sensors if necessary to achieve state transition detection. Catnap [14] allowed sensors to sleep during data transfers, and exploited high bandwidth wireless interfaces by combining small gaps between packets into meaningful sleep intervals. On the other hand, Collaborative energy management was addressed in [15], where network-wide energy decision making is enabled. Finally, our previous work [16] proposed a generic network management framework through negotiations among queries and network resource, by estimating the network capacity in a QoI friendly fashion and monitoring the level of received QoI in real-time, but without any of the energy issues addressed thus far.

Regarding the energy management research for traditional sensor networks, work [17] was the first work to use the mathematical paradigm of the Gur Game [7], [8] to dynamically adjust the optimal number of sensors to operate. This approach provides a useful distributed approach while the optimal operational status was achieved through a few steps of iteration. Later, the Gur Game was extended in [18], where an energy-aware algorithm was developed, and the periodic sleeping mechanism was introduced. Ref. [19] also used a Gur Game formulation to maximize the number of regions covered by sensors. Apart from the Gur Game approach, paper [20] proposed a distributed low power scheduling algorithm for sensor nodes to determine its active time slots in a TDMA mechanism working on top of a slotted CSMA network. In [21], the authors improved the overall performance of the WSNs through local collaborations of neighbor nodes, and provide a more efficient duty-cycle management solution; [22] proposed a distributed topology control technique to schedule nodes' wake-up time slots. However all these duty-cycling schemes lack a clear notion of QoI, and if under the context of participatory sensing, the impacts from the human behavior and the revenue from the network operator should be also considered; and these primarily drive our research in this paper.

III. System Model

This section presents a formal model for describing our efficient network management system. We consider a scenario as shown in Fig. 1 comprising both the smartphone user 1 as a querier and a set of N smartphone users within the proximity of user 1's site of interest, as the participants, denoted as $\mathcal{N} = \{i = 1, 2, \ldots, N\}$. Let q represent the querier's query, and let $\mathcal{Q}$ be the collection of all currently outstanding queries. The query q is processed by the network operator and results in a request for a sensing services from participant users. Such service requests may include, for example, retrieval of image(s) from a tourist attraction, of information about an event occurrence, traffic conditions, etc.[1] Each request q is associated with one or more high-level QoI attributes, such as the required degree of query understanding, where different types of information from multiple sensing sources collaboratively provide a *single* view of the query understanding. In other words, we provide a mapping from the retrieved information to the overall degree of query understanding, e.g., realtime videos are more likely to provide a higher degree of understanding than sending texts alone.

We use the superscript r to denote a QoI attribute value *required* (and declared) by a query upon their arrival for service, and a for that value *attained* after the participatory sensing, e.g., let u_q^r and u_q^a denote the required and attained degree of event understanding, respectively, regarding the query q. Finally, we denote the types of contextual information users could contribute as the set $\mathcal{C}$ (of size $|\mathcal{C}|$), which include, but not limited to, images and video clips with different resolutions, voice clip and text messaging, etc. For each smartphone user, we further denote $c_q^i \in \mathcal{C}, \forall i \in \mathcal{N}$, as the *recommended* type of information by the proposed automaton (see Section VII) embedded on each smartphone. However, we are also interested in exploring the potential human impacts on the decision-making process. In other words, the recommended action c_q^i may not be finally taken, but the user may choose $\hat{c}_q^i$ instead. We model this human behavior in Section VI. After all information is gathered from participants, the network operator aggregates and passes it to the querier. Clearly, different combinations of information sources would result in different degrees of understanding the service, like video and image would be more likely better than texts alone. We next in Section IV introduce a metric to measure this degree of satisfaction between the attained information and its required level.

[1]For simplicity reasons, for the rest of the presentation we assume that each smartphone user will help with one query at a time.

IV. QoI Satisfaction Index

For convenience, we start with the satisfaction index from [16], adjusted to the system model of this paper. As its name implies, this index is used to describe the level of QoI satisfaction the queries received from the participatory sensing among smartphone users. It is applicable to each query $q \in \mathcal{Q}$ and for a specific QoI attribute u, the attained measurement is computed as:

$$u_q^a = f\left(\{u_q^{i,a}\}_{i \in \mathcal{N}}\right), \quad \forall q \in \mathcal{Q}, u \in \underline{u}, \tag{1}$$

where $\underline{u}$ represents multi-dimensional QoI requirements, one of which u could be the event understanding requirement. Mapping f denotes the information fusion algorithm running at the network operator, aggregating multiple pieces of information to a single view of the event. Then, the network-wide QoI satisfaction index for QoI attribute u is denoted as:

$$\theta_q^u \triangleq \tanh\Big(k_\theta \ln \frac{u_q^a}{u_q^r}\Big), \quad \forall q \in \mathcal{Q}, u \in \underline{u}, \tag{2}$$

where k_θ denotes a scaling factor. The selection of the functions $\ln(\cdot)$ and $\tanh(\cdot)$ is rather arbitrary but result in the intuitively appealing and desirable behavior for satisfaction.

Therefore, the overall QoI satisfaction index $\mathrm{I}_q^{\mathrm{QoI}}$ for any query with multiple-QoI requirements during the service of the participatory sensing can be defined by taking the minimum of all QoI satisfaction indexes for each QoI attribute $u \in \underline{u}$, i.e.,

$$\mathrm{I}_q^{\mathrm{QoI}} = \min_{u \in \underline{u}} \theta_q^u \in (-1, 1), \quad \forall q \in \mathcal{Q}. \tag{3}$$

It follows immediately from the definition of the QoI satisfaction index that:

Lemma 4.1: For any participatory sensing query, its (multiple) QoI requirements are simultaneously satisfied if and only if $\mathrm{I}_q^{\mathrm{QoI}} \in [0, 1), \forall q \in \mathcal{Q}$.

V. Credit Estimation and Allocation

One problem of using participatory sensing for information retrieval is to motivate the users' participation. Similar to [11], we use the *credits* to encourage the participation, but we explicitly link the amount of credits payable to the users with

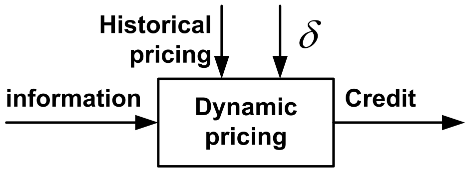

Fig. 2. The block diagram of the proposed dynamic pricing scheme.

the revenue the network operator may gain through adjusting its inherited pricing scheme. Therefore, this section deals with estimating the amount of credit that the network operator allocates through dynamic pricing schemes to participants. From the network operator's perspective, the total revenue needs to be maximized while meeting the satisfactory levels of the credit expectations for all participants. Nevertheless, the users may not disclose their credit expectations in advance to the network operator before the service of the query, or usually users may only vote for satsifaction/dissatifaction after the service and the credit is paid, like the telephone customer services. This primarily drives the need of the network operator to predict the expected future credits through the payment history, and meet the users' expectations during the voting.

Since queries sequentially arrive for service, we employ the exponential smoothing method taking only the most recent payment history to predict the next expected credit from participants. Let $\hat{\varphi}^{i,r}_{q-1}, \varphi^{i,r}_{q-1}, \forall i \in \mathcal{N}$, denote the predicted and actual credit requirement of the previous query $q-1$, respectively. Then, the new expected credit $\hat{\varphi}^{i,r}_q$, is estimated through:

$$\hat{\varphi}^{i,r}_q = (1-\mu)\hat{\varphi}^{i,r}_{q-1} + \mu\varphi^{i,r}_{q-1}, \quad \forall i \in \mathcal{N}, q \in \mathcal{Q}, \tag{4}$$

where $\mu \in (0,1)$ is the weight factor. Next is to decide the pricing plan at the network operator to determine the exact amount of credits payable to each participant, and we assume it is represented by the mapping $\omega_q : \hat{c}^i_q \to \varphi^{i,a}_q$. The goal of the network operator is to minimize the sum of mean square errors incurred by imperfect credit predications in (4) through adapting the pricing plan ω_q over time. Given that the change of the pricing plan is not favored by the network operator, we formulate the following optimization problem as:

$$\omega^*_q = \arg\min_{\omega_q} \frac{1}{N} \sum_{i\in\mathcal{N}} \left\{\hat{\varphi}^{i,r}_q - \omega_q(\hat{c}^i_q)\right\}^2$$
$$\text{subject to:} \left\| \frac{\omega_q - \omega_{q-1}}{\omega_{q-1}} \right\| \leq \delta, \tag{5}$$

where δ denotes the maximum allowed percentage of adaptation from the network operator. The inputs to this optimization problem are the retrieved information $\hat{c}^i_q$ and estimated credit requirements $\hat{\varphi}^{i,r}_q$, while the output is the overall pricing plan ω^*_q rewarding the contributions of the participants. Fig. 2 shows the block diagram of the proposed dynamic pricing scheme.

We conclude this section by introducing, in a manner analogous to the QoI satisfaction index, the *credit satisfaction index*, $\mathrm{I}^{i,\omega}_q, \forall i \in \mathcal{N}$, to represent the degree of credit satisfaction for individual smartphone user, and it is computed as:

$$\mathrm{I}^{i,\omega}_q \triangleq \tanh\left\{k_\omega \ln \frac{\varphi^{i,a}_q}{\varphi^{i,r}_q}\right\}, \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, \tag{6}$$

where $\varphi^{i,a}_q = \omega^*_q(\hat{c}^i_q)$ and k_ω is a scalar. The higher value of this index represents the higher degree of credit satisfaction for user i. We show in the next section how the QoI and credit expatiation index are used to link the network operator and smartphone users for both the energy and QoI-aware network management.

VI. Network Management Framework

In this section, we describe the novel framework of the proposed efficient network management approach, which is collaboratively achieved by the network operator (who coordinates the participatory sensing tasks) and smartphone users (who make their decisions in a distributed way).

Without loss of generality, suppose a smartphone user generates the query q with multi-dimensional QoI requirements and sends the service request to the network operator through access communication networks like 3G, after which the request propagates towards (candidate) participant users in the vicinity of the site of interest. As discussed earlier, there is no central controller controlling the decision of participation for each smartphone user; nevertheless, the decision is likely to be influenced by both the network operator through incentives, or the credits in our proposal, and the human behavior. For each user, we use the mathematical model of the Gur Game [7], [8], [17] to *iteratively* achieve the long-term balance between the maintenance of the energy and the support of QoI, as presented in Section VII. We preset the total number of iterations as J.

We next describe the overall structure of the proposed network management framework. For query q at each iteration step $j \in \{1, 2, \ldots, J\}$, the network operator runs the embedded information fusion algorithm in (1). Then, it computes and outputs the level of achieved QoI, or $\mathrm{I}^{\mathrm{QoI}}_q(j)$ in (3), and the credit expectation index, or $\mathrm{I}^{i,\omega}_q$ in (6). Note that the latter index does not change over iterations. These will be used as the inputs to the Gur Game embedded in each smartphone (see Section VII) to compute its energy-consumption state at step $j+1$. Next, the network operator collects the new participating information and compute the attained level of QoI again, triggering the new round of iteration. After a few steps of iterations, the output of the Gur Game will recommend each smartphone user the type of contextual information, denoted as $c^i_q \in \mathcal{C}, \forall i \in \mathcal{N}$.

While the outcome of the Gur Game recommends the optimal type of contextual information c^i_q that the smartphone should send, its (human) user may decide otherwise. We next study the impact of the human action. Specifically, we model the human behavior by a simple ON-OFF process (see Fig. 3):

$$\hat{c}^i_q = \begin{cases} c^i_q, & \text{if in "agree" state,} \\ \emptyset, & \text{others,} \end{cases} \tag{7}$$

where $\hat{c}^i_q = \emptyset$ represents that users decide to remain idle. One example is to implement a human interface, like button

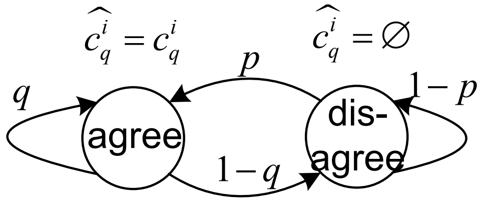

Fig. 3. An On-Off user action.

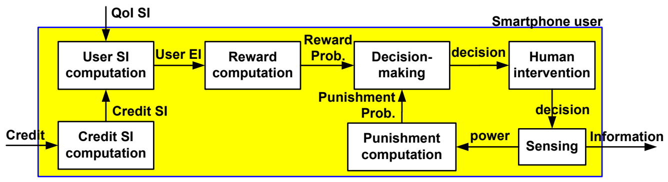

Fig. 4. The flow of the automaton building block of each smartphone, which decide the duty cycling decisions of the user.

click, on the smartphone to ask for decision approval from users. Then, statistically the inherited transition matrix could be represented by:

$$P = \begin{pmatrix} 1-p & p \\ 1-q & q \end{pmatrix} \tag{8}$$

where the first entry is the disagreement state and the second entry is the agreement state.

Finally, the network operator pays off the credits to the participants according to (5) and receives the service fee from the querier. The amount of service fee, denoted by φ_q, should be at least the amount paid to all participants to keep gaining the revenue, as:

$$\varphi_q \geq \sum_{i \in \mathcal{N}} \varphi_q^{i,a}, \tag{9}$$

or equivalently the network operator generates the revenue:

$$\text{revenue} = \varphi_q - \sum_{i \in \mathcal{N}} \varphi_q^{i,a}. \tag{10}$$

Detailed descriptions of how retrieved information $\hat{c}_q^i$ is obtained from each user is presented in the following Section VII.

VII. Gur Game-based Distributed Energy Control

In this section, we describe the proposed distributed energy management scheme for each smartphone user within the proximity of the site of interest, through the mathematical model of the Gur Game. Followed by the introduction of the Gur Game, we propose our pay-off structure and present how the decision is made distributedly. Fig. 4 shows the flow diagram of the proposed automaton for each smartphone user, which decides its duty cycling decision $\hat{c}_q^i, \forall i \in \mathcal{N}$.

A. The Gur Game

The mathematical model of the Gur Game [17] adopted was first used to power on a desired number of wireless sensors in a region, where each sensor votes distributedly for being active at each iteration, and the gradually converge through a few steps of iterations. We now briefly introduce the fundamental concept and how our proposed system behaves.

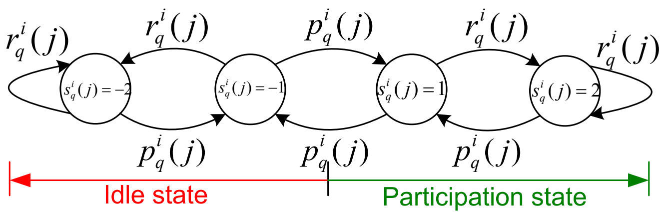

Fig. 5. An example of the Gur Game with associated memory size $M = 2$, where positive number states give the corresponding output of the contextual information for user i, e.g., text message, low resolution image, or high resolution image. Negative numbers state represent "no participation" decision of the user.

We assume that *all* smartphrones are associated with a finite discrete-time automaton with the same length of memory M, as shown in Fig. 5. This automaton is a single nearest-neighbor Markov chain of memory size $2M$. Starting from the left-most state, the states are numbered from $-M$ to -1, then followed by numbering 1 to M to the right-most state. We denote these $2M$ energy consumption states as $\mathcal{S} = \{\pm s | s = 1, 2, \ldots, M\}$. This partitions the overall Markov chain into negative numbered states, which represent the "`idle`" decision of the smartphone users (or no participation), and positive numbered states, which represent the "`participation`" decision of smartphone users with corresponding output of the type of contextual information to be contributed c_q^i. As shown in Fig. 5, c_q^i is illustrated as the *recommended* action, or the result of moving to state $s_q^i \in \mathcal{S}$.

For each query $q \in \mathcal{Q}$, we preset the number of iterations J, or transitions among energy-consumption states for each user i, required to reach the overall system convergence. These transitions are driven by the pay-off function and work in a greedy fashion. Without loss of generality, let $r_q^i(j)$ and $p_q^i(j)$, where $j = \{1, 2, \ldots, J\}$, denote the reward and penalty user i received from iteration step $j-1$ to j before the new decision for step j is made, respectively. After each iteration, the current state of the smartphone would transit probabilistically according to the received pay-off function to the next state, i.e., $s_q^i(j) = s_q^i(j-1) + 1$ or $s_q^i(j) = s_q^i(j-1) - 1$. Higher values of performance pay-off function drive the finite state automaton to move towards two edge states $-M$ and M. However if $s_q^i(j-1)$ happens to be the left-most or right-most state $-M$ or M, then the next energy-consumption state $s_q^i(j)$ is only allowed to be in its own state or the adjacent state. In a summary, it is interesting to see that the punishment behavior will make the energy consumption state of the smartphones shift the chain towards middle while a rewarding behavior will shift it outward.

B. The Pay-off Structure

It is desired that the goal of our proposed energy management approach is to prolong the lifetime of *all* smartphones by reducing the energy consumption rate, to provide the satisfactory QoI experience to all queries, and to meet the users' *credit expectation* simultaneously. Meeting these expectations would give higher probability for participated smartphone users to contribute in the following queries, while

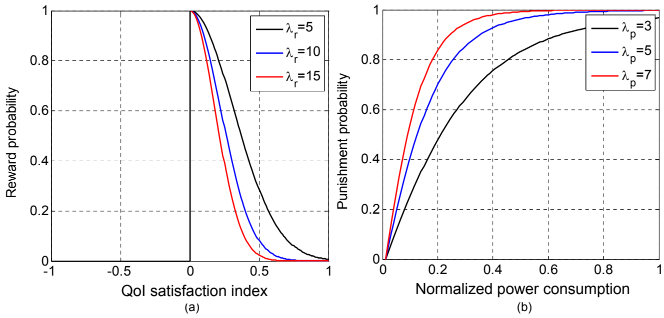

Fig. 6. An example of the probability mappings for (a) the reward and (b) the punishment, respectively.

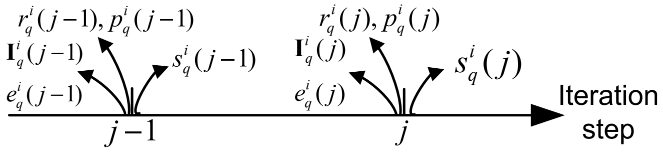

Fig. 7. An illustrative example for the change of the energy-consumption states of any user i.

failing to do so would probably make the participatory sensing task itself difficult.

1) User Experience Index: From each user's perspective, the overall query satisfaction should consider both the QoI satisfaction index and the credit satisfaction index. We have:

$$\mathrm{I}_q^i(j) \triangleq \min\left(\mathrm{I}_q^{\mathrm{QoI}}(j), \mathrm{I}_q^{i,\omega}\right), \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, j, \tag{11}$$

and we will refer to $\mathrm{I}_q^i(j)$ as the "user experience index". The higher value of this index means the better support of the querier's demand while meeting participants' credit expectation, which would be the most favorable win-win situation for the query.

2) Reward Structure: Given the defined user experience index for each iteration step j, we next show how the reward structure for the Gur Game automaton is structured. We have:

$$r_q^i(j) = \phi_r\left(\mathrm{I}_q^i(j)\right), \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, j, \tag{12}$$

where let $\phi_r : \mathbb{R} \to [0, 1]$ denote the mapping from the attained user experience index to the reward probability. Fig. 6(a) shows an example of the realization of ϕ_r, where parameters are chosen as $\lambda_r = 5, 10, 15$. Mathematically, we have:

$$r_q^i(j) = \begin{cases} \exp^{-\lambda_r \mathrm{I}_q^i(j)^2}, & \text{if } \mathrm{I}_q^i(j) \in [0, 1), \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

We can see from (13) that instead of favoring the highest user experience with $\mathrm{I}_q^i(j) \approx 1, \forall j$, the proposed reward structure aims to provide only the satisfactory level $\mathrm{I}_q^i(j) = 0$, i.e., meeting the querier's requirement while maintaining the energy for future services. Theoretically, the candidate users in the Gur Game will collaboratively achieve the highest pay-off probability (both the reward and the punishment) through iterations. We introduce the penalty structure capturing the energy consumption upon information contribution in the next section.

3) Penalty Structure: Since the type of contextual information the user contributes changes over time, we propose to use the normalized energy consumption $e_q^i(j)$, which denotes the amount of energy usage from iteration step $j-1$ to j due to the last action (although not taken) $\hat{c}_q^i(j-1)$. $e_q^i(j)$ is computed as the ratio between the energy usage $\gamma(\hat{c}_q^i(j-1))$ and the maximum energy consumption over all types of the information $\max_{c\in\mathcal{C}} \gamma(c)$, where let $\gamma(\cdot)$ denote the energy consumption mapping for information $c \in \mathcal{C}$. We have:

$$e_q^i(j) = \frac{\gamma(\hat{c}_q^i(j-1))}{\max_{c\in\mathcal{C}} \gamma(c)}, \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, j. \tag{14}$$

Using $e_q^i(j)$ as the input to the penalty probability mapping $\phi_p : \mathbb{R} \to [0, 1]$ for each iteration step yields:

$$p_q^i(j) = \phi_p\left(e_q^i(j)\right), \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, j, \tag{15}$$

where larger energy usage due to information contribution $\hat{c}_q^i(j-1)$ would result in higher penalty, and lower energy usage is otherwise favorable. Fig. 6(b) shows an example of the realization of ϕ_p, where parameters are chosen as $\lambda_p = 3, 5, 7$. Mathematically, we have:

$$p_q^i(j) = \begin{cases} \tanh\left(\lambda_p \ln e_q^i(j)\right), & \text{if } e_q^i(j) \geq 0, \\ 0, & \text{otherwise.} \end{cases} \tag{16}$$

We can see from (17) that the proposed penalty structure penalizes the higher energy usage while favoring the minimum energy consumption for any query service. Together with (13), the reward and penalty structures trade off in providing the satisfactory QoI experience to the query while spending the minimum amount of energy in the service. We next introduce how these structures are used in the distributed decision-making process.

C. The Decision-Making Process

Given the pay-off structure in the previous section, next we show the proposed iterative and distributed decision-making process for each smartphone user i. Suppose the next decision to make is at iteration j, see Fig. 7, and its residing state is the same as the previous state $s_q^i(j-1)$. The outcome of the j^{th} decision would transit the state to $s_q^i(j)$ and corresponds to a recommended action $c_q^i(j)$. After J iterations, the users would make the final decision upon participation action to $\hat{c}_q^i$. The pseudocode in Algorithm 1 illustrates the steps of iterations.

It is worth noting that the proposed Gur Game approach is fully distributed. Users neither need to forecast their own energy-consumption states nor exchange any information from other participants. Instead, they use the trial-and-error method to produce the best result at each step and iteratively achieve the overall optimum [7], [8].

VIII. Performance Evaluation

We access the proposed scheme under a simple but representative participatory sensing scenario, where event of interest is an outdoor performance and the pertinent contextual information can be provided by text messages, pictures, or

Algorithm 1 : Distributed Gur Game

$\forall q \in \mathcal{Q}$, Initialize: J
for all $j = 1, 2, 3, \ldots J$ **do**
  for all smartphone user $i \in \mathcal{N}$, **do**
    compute $\mathrm{I}_q^i(j)$ in (11);
    compute $e_q^i(j)$ in (14);
    compute $r_q^i(j)$ and $p_q^i(j)$ in (12) and (15);
    uniformly generate a random number `seed`$\in [0,1]$;
    state transition condition:

$$\begin{cases} s_q^i(j) = s_q^i(j-1) + 1, & \text{if } \texttt{seed} \geq \frac{r_q^i(j)}{r_q^i(j)+p_q^i(j)}, \\ s_q^i(j) = s_q^i(j-1) - 1, & \text{otherwise,} \end{cases}$$

    where if $s_q^i(j-1) = \pm M$, then $s_q^i(j)$ is only allowed to be in its own state or the adjacent state.
    output action $c_q^i(j)$;
  end for
end for
Return: final recommended action $c_q^i \leftarrow c_q^i(J), \forall i \in \mathcal{N}$.

even videos from smartphone users. For simplicity reasons, we do not simulate this information in detail, but we assume that the querier would have different capabilities in consuming this information, yielding a different *degree* of understanding the event. Therefore, we use the `degree of understanding`, "u", denoted as $u_q^r, \forall q \in \mathcal{Q}$, as the only *required* QoI metric, randomly generated from the lower bound 0.8 to the upper bound 1, where the higher u_q^r represents higher the required level of contextual information, e.g. the video. To this end, we are able to reduce the contextual information set $\mathcal{C}$ to the size of 1. Query-wise, we assume that the duration of the proposed iterative energy management process is relatively small compared with the inter-arrival time of the queries, so that there is only one query serving in the network at any time. We set up our simulator by randomly deploying $N = 30$ smartphone users in a 200×200 meter square, each of which has an initial, equal energy reserve $\mathcal{E}$, so that $N\mathcal{E}$ is the overall energy reserve for the entire network. Lastly, we set the parameter of the expected credit from each smartphone user to a constant $\varphi_q^{i,r} = 1, \forall i \in \mathcal{N}, \forall q \in \mathcal{Q}$. Finally, we employ a location-based detection model [23] using physical properties of the smartphones, where individual attained probability of detection $u_q^{i,a}$ from smartphone-to-query distance d_q^i is achieved by:

$$u_q^{i,a} = \exp\left\{-\frac{0.5}{\gamma(c_q^i)}\left(d_q^i\right)^{1.2}\right\}, \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}. \tag{17}$$

By setting $u_q^{i,a} = 1$, each user computes its power consumption in achieving best probability of detection, and Fig. 8 shows an example of the power usage.

After the iterations of the Gur Game, let $\mathcal{N}_q \in \mathcal{N}$ denote the final set of users chosen to participate the query $q \in \mathcal{Q}$, each of which achieves best detection probability 1. Next, we adopt a simple heuristic to tie the participants' responses to

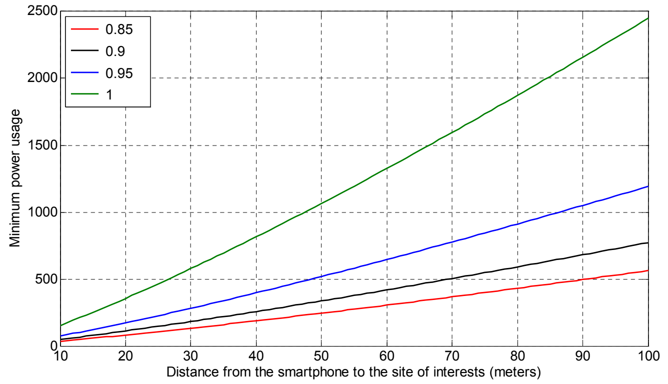

Fig. 8. An example of minimum power usage to achieve different probability of detection requirements, w.r.t. different distances from the smartphone to the site of interest.

the querier's query. We will write:

$$u_q^a = \tanh\left(0.8 \ln |\mathcal{N}_q|\right), \quad \forall q \in \mathcal{Q}, \tag{18}$$

implying that the more smartphones participate and send pertinent contextual information, the more accurately and comprehensively the querier's query will be answered, e.g., when $\mathcal{N}_q = 1$ the attained degree of understanding is only 0, while it saturates with level 1 when $|\mathcal{N}_q| = N$. An example could be the query of an ongoing event, where images taken from different angles enforce the degree of user's understanding. Finally, the QoI satisfaction index is computed as in (3).

We first show the convergence of the proposed distributed Gur Game approach by showing the change of the received QoI satisfaction index over time in Fig. 9(a), where totally 20 queries are simulated and memory size of $M = 3$ of the Gur Game for each smartphone is used. A detailed look at one query is demonstrated in Fig. 9(b). We observe that for the fixed M, the received QoI satisfaction index iteratively converges to the lower-bound borderline satisfaction, or: $\mathrm{I}_q^{\mathrm{QoI}} = 0, \forall q \in \mathcal{Q}$ within small number of steps (in this example 32 steps). Achieving $\mathrm{I}_q^{\mathrm{QoI}} = 0$ requires the minimum number of sensors involved into participation while preserving much energy for the following queries; however although the proposed scheme could not guarantee this "optimum", we still achieve the suboptimum (in terms of QoI) with very fast convergence. If considering the possible combinations of the Markov states for N sensors M^N, we conclude that the number of required steps in our approach is quite efficient.

Next, we explore the impacts of both the memory size and the network size on the convergence rate, in Fig. 10. It is observed that for the fixed network size, the larger the memory size of the Gur Game is, the more the required number of steps. Meanwhile, for the fixed memory size, the convergence rate increases with the increase of the number of users in a fixed geographic region. To cope with this scalability issue, we may reduce the set of participants to $N = 30$ in total (however the number of people around the site of event occurrence where the network operator may potentially communicate with could be more), since users far apart would consume much more

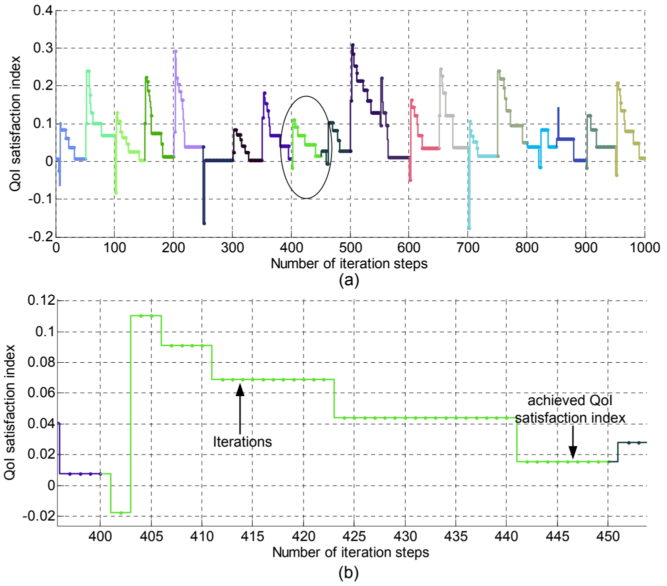

Fig. 9. (a) convergence rate for 20 simulated queries, where different colors represent different queries, and (b) convergence rate for a specific query.

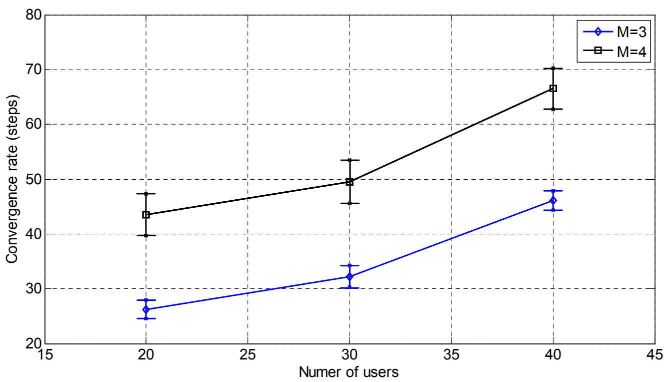

Fig. 10. The impact of memory size and network size on the convergence rate, with 95% confidence interval.

energy in participating the query. In the following simulations, we fix $M = 3$ and $N = 30$.

We compare our algorithm with the optimal sensing scenario, and the worst-case sensing scenario. For the former, it achieves the lower-bound energy usage and QoI satisfactions, by selecting the nearest and minimum number of neighbors with regards to the site of interest to help with participatory sensing according to their locations. And thus it is guaranteed that the users chosen would use the minimum power consumption. For the latter, all users are forced to participate in any query so that best QoI is achieved with the compromise of the larger energy usage.

Fig. 11(a) shows the histogram of the attained QoI satisfaction index by simulating 800 tasks. It can be seen that more than 93% of the tasks receive the satisfactory QoI experience, or the proposed approach successfully guarantees very low percentage of QoI failures, or the QoI outage probability. Compared with the optimal solution where the received QoI satisfaction index should be highly concentrated to 0 (borderline), our proposal achieves the suboptimum. To

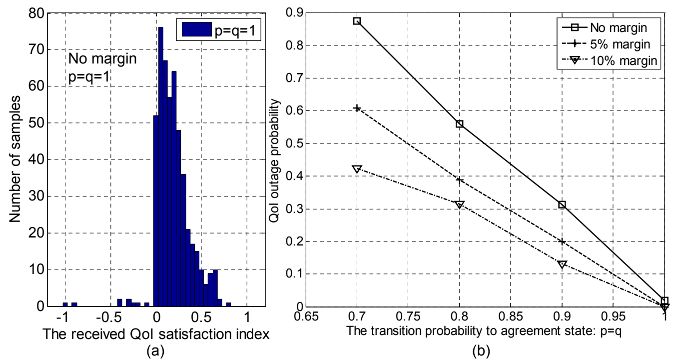

Fig. 11. (a) The histogram of the received QoI satisfaction index when $p = q = 1$, and (b) the impact of the human intervention on the QoI outage probability w.r.t. different p, q.

further balance the human intervention and provide lower QoI outage, we introduce a margin ϵ on the required degree of understanding, or $u^r_{q,\text{margin}} = (1+\epsilon)u^r_q, \forall q \in \mathcal{Q}$, before the distributed Gur Game starts, so that the larger number of smartphones are recommended for participation with the compromise of potentially higher energy consumption per query. Fig. 11(b) demonstrates this impact by fine tuning the transition matrix parameters $p = q$ in (8) between disagreement and agreement. It is interesting to observe that for $p = q = 1$, i.e., without any margin reserved for QoI requirement, our scheme achieves very low QoI outage probability, however it increases sharply to the higher levels if human intervention is considered $p = q < 1$. This is primarily because the proposed scheme helps choose the minimum amount of smartphone users for participation to achieve the suboptimal degree of understanding; however, if (at least) one of the chosen users decides to give up, the attained QoI after the information fusion would significantly deteriorate and drop below the required level. This explains why we need to introduce this margin to balance the human intervention.

Fig. 12 shows the simulation result for the change of the credit allocation and expectation over time, where we preset the threshold for dynamic pricing margin $\delta = 0.05$. It is observed that the proposed approach successfully tracks the expected per-smartphone credit expectation $\varphi^{i,r}_q = 1, \forall i \in \mathcal{N}$, however the detailed change is still observable between the band $(1 \pm \delta)$, while the total allocated credit is close enough to the total required for all smartphone users, i.e., we meet the credit expectations of the users.

Finally, Fig. 13 illustrates the change of the percentage of the remaining energy for three scenarios, where we observe that the proposed energy-management scheme successfully achieve the suboptimal solution with significant gains if compared with the full participation case, i.e., when the worst-case full participation solution drain out the energy preserve of the WSN, the proposed scheme has still 82% of the overall energy left for the future tasks. Even compared with the optimal sensing, the gap is relatively very small, i.e. only 4% higher than our scheme. The suboptimum is achieved primarily due to distributed selection of the set of sensors into participation

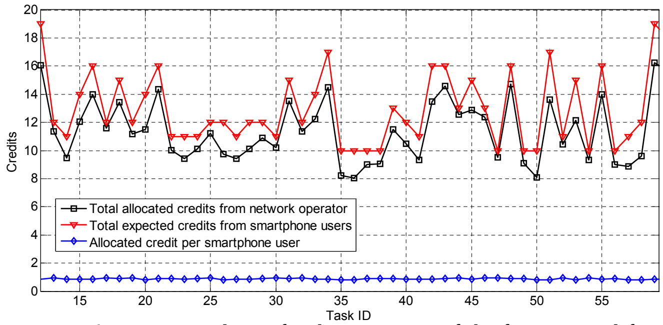

Fig. 12. A system simulation for the estimation of the future reward from the historical data.

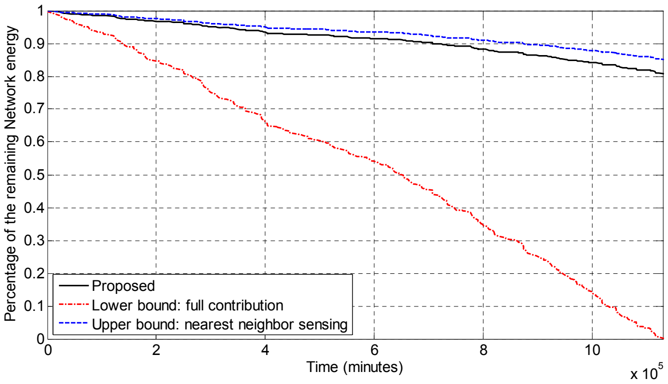

Fig. 13. The remaining energy of the three schemes.

which may not be the optimal set of sensors who are nearest to the event; and thus the power consumption per-task could be sometimes higher.

IX. Concluding Remarks

In this paper, we proposed a novel efficient network management framework for the emerging user-centric application, the participatory sensing. We tackled the overall network management problem as two subproblems, for the network operator and for the individual smartphone user. For the former, we explicitly consider the revenue maximization and QoI support through a constrained optimization problem. We also studied the impact of human behavior on the participatory sensing decision-making process. For the latter, we user the mathematical framework of the Gur Game to propose a distributed QoI-aware energy-management scheme for smartphones. The fundamental trade-off between the maintenance of the smartphone energy and the support of the QoI experience is fully exploited and addressed. Finally, extensive numerical results on a complete participatory sensing scenario show the proposed framework can successfully guarantee less than 7% QoI outage, saves 80% of the energy reserve if compared with the lower bound solution, and achieves the suboptimum with only 4% gap if compared with optimal solution.

In the future work, we are planning of building a testing prototype using Android phones as mobile clients and empirically evaluate the human factors and the other system performance. We are also working on a complete distributed solution for participatory sensing of pure mobile-to-mobile systems. This will be important and useful for opportunistic network or delay tolerant network scenarios. We believe our work is a fundamental stone for incentive-based participatory sensing, and a lot of work can follow.

References

[1] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, and H. Balakrishnan, "The pothole patrol: using a mobile sensor network for road surface monitoring," in *ACM MobiSys'08*, Breckenridge, CO, USA, 2008, pp. 29–39.

[2] P. Mohan, V. N. Padmanabhan, and R. Ramjee, "Nericell: rich monitoring of road and traffic conditions using mobile smartphones," in *ACM SenSys'08*, Raleigh, NC, USA, 2008, pp. 323–336.

[3] "What's invasive! community data collection," http://whatsinvasive.com.

[4] S. Gaonkar, J. Li, R. R. Choudhury, L. Cox, and A. Schmidt, "Microblog: sharing and querying content through mobile phones and social participation," in *ACM MobiSys'08*, Breckenridge, CO, USA, 2008, pp. 174–186.

[5] M. E. Johnson and K. C. Chang, "Quality of information for data fusion in net centric publish and subscribe architectures," in *FUSION'05*, July 2005.

[6] C. Bisdikian, L. M. Kaplan, M. B. Srivastava, D. J. Thornley, D. Verma, and R. I. Young, "Building principles for a quality of information specification for sensor information," in *FUSION 2009*, July.

[7] M. Tsetlin, "Finite automata and modeling the simplest forms of behavior," Ph.D. dissertation, V.A. Steklov Mathematical Institute, 1964.

[8] B. Tung and L. Kleinrock, "Distributed control methods," in *2nd Int'l Sym. on High Perf. Dist. Comp.*, Jul 1993, pp. 206 –215.

[9] Z. Yang, B. Zhang, J. Dai, A. Champion, D. Xuan, and D. Li, "E-smalltalker: A distributed mobile system for social networking in physical proximity," in *IEEE ICDCS'10*, Genoa, Italy, June 2010.

[10] M. B. Kjaergaard, J. Langdal, T. Godsk, and T. Toftkjaer, "Entracked: energy-efficient robust position tracking for mobile devices," in *ACM MobiSys'09*, Kraków, Poland, 2009, pp. 221–234.

[11] J. Lee and B. Hoh, "Sell your experiences: A market mechanism based incentive for participatory sensing," in *IEEE PerCom'10*, 2010.

[12] G. Werner-Allen, S. Dawson-Haggerty, and M. Welsh, "Lance: optimizing high-resolution signal collection in wireless sensor networks," in *ACM SenSys'08*, Raleigh, NC, USA, 2008, pp. 169–182.

[13] Y. Wang, J. Lin, M. Annavaram, Q. A. Jacobson, J. Hong, B. Krishnamachari, and N. Sadeh, "A framework of energy efficient mobile sensing for automatic user state recognition," in *ACM MobiSys'09*, Kraków, Poland, 2009, pp. 179–192.

[14] F. R. Dogar, P. Steenkiste, and K. Papagiannaki, "Catnap: Exploiting high bandwidth wireless interfaces to save energy for mobile devices," in *ACM MobiSys'10*, San Francisco, CA, USA, 2010.

[15] G. W. Challen, J. Waterman, and M. Welsh, "Idea: Integrated distributed energy awareness for wireless sensor networks," in *ACM MobiSys'10*, San Francisco, CA, USA, 2010.

[16] C. H. Liu, C. Bisdikian, J. W. Branch, and K. K. Leung, "QoI-aware wireless sensor network managment for dynamic multi-task operations," in *IEEE SECON'10*, Boston, MA, USA, 2010.

[17] R. Iyer and L. Kleinrock, "QoS control for sensor networks," in *IEEE ICC'03*, June 2003, pp. 517 – 521.

[18] L. Zhao, C. Xu, Y. Xu, and X. Li, "Energy-aware QoS control for wireless sensor network," in *1st IEEE Conf. on Industrial Electronics and App.*, May 2006, pp. 1 –6.

[19] S. I. Nayer and H. H. Ali, "A dynamic energy-aware algorithm for self-optimizing wireless sensor networks," *Springer Lecture Notes in Computer Science: Self-Organizing Systems*, vol. 5343, pp. 262–268, 2008.

[20] T. Kim, N. Park, P. K. Chong, J. Sung, and D. Kim, "Distributed low power scheduling in wireless sensor networks," in *IEEE ISWPC'07*, Feb. 2007.

[21] J. Wu and Z. Sun, "Distributed duty-cycle management for dependable wireless sensor networks," in *UK Perf. Engr. Workshop'08*, 2008.

[22] Y. Zhou and M. Medidi, "Sleep-based topology control for wakeup scheduling in wireless sensor networks," in *IEEE SECON'07*, June 2007, pp. 304 –313.

[23] S. S. Iyengar and A. Elfes, "Occupancy grids: a stochastic spatial representation for actie robot perception," *Autonomous Mobile robots: Perception, Mapping, and Navigation*, vol. 1, pp. 60–70, 1991.