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Wireless sensor deployment for collaborative sensing with mobile phones

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ABSTRACT

Wireless sensor networks have been widely deployed to perform sensing constantly at specific locations, but their energy consumption and deployment cost are of great concern. With the popularity and advanced technologies of mobile phones, participatory urban sensing is a rising and promising field which utilizes mobile phones as mobile sensors to collect data, though it is hard to guarantee the sensing quality and availability under the dynamic behaviors and mobility of human beings. Based on the above observations, we suggest that wireless sensors and mobile phones can complement each other to perform collaborative sensing efficiently with satisfactory quality and availability.

In this paper, a novel collaborative sensing paradigm which integrates and supports wireless sensors and mobile phones with different communication standards is designed. We propose a seamless integrated framework which minimizes the number of wireless sensors deployed, while providing high sensing quality and availability to satisfy the application requirements. The dynamic sensing behaviors and mobility of mobile phone participants make it extremely challenging to estimate their sensing quality and availability, so as to deploy the wireless sensors at the optimal locations to guarantee the sensing performance at a minimum cost. We introduce two mathematical models, a sensing quality evaluation model and a mobility prediction model, to predict the sensing quality and mobility of the mobile phone participants. We further propose a cost-effective sensor deployment algorithm to guarantee the required coverage probability and sensing quality for the system. Extensive simulations with real mobile traces demonstrate that the proposed paradigm can integrate wireless sensors and mobile phones seamlessly for satisfactory sensing quality and availability with minimized number of sensors.

1. Introduction

The advancement of recent technologies in embedded systems and low power wireless communications turned wireless sensor networks into reality. A wireless sensor network (WSN) consists of spatially distributed autonomous sensing devices which cooperatively monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion or pollutants at different locations. Traditional sensor networks involve a number of stationary sensors being deployed carefully at chosen locations for a particular technological purpose. For example, the structural health of buildings in an earthquake-prone area can be monitored by deploying a network of dedicated wireless sensor nodes equipped with accelerometers on the buildings. Applications of WSNs include habitat monitoring, structure monitoring, health monitoring, object tracking and fire detection [1]. Although individual sensor node is not very expensive, large deployment of sensor nodes in the network could make the total cost considerably high.

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Apart from sensors, mobile phones are becoming increasingly popular and more powerful. Some mobile phones are even equipped with various sensing capabilities, such as detecting sound, motion, location, etc. Recently, an alternative paradigm has emerged for accomplishing large-scale sensing, known as participatory sensing or urban sensing [2,3]. The key idea of participatory sensing is to leverage the existing sensing and communication infrastructure to achieve the goal of sensing by having network users providing and sharing the necessary sensing information. Mobile phone users could collect data at different time and locations when they move around. Similarly, MetroSense [3,4] envisioned a people-centric paradigm for urban sensing at the edge of the Internet, at very large scale based on an opportunistic sensor networking approach. A number of participatory sensing applications have emerged in recent years. CarTel [5] is a system that uses mobile sensors mounted on vehicles to collect information about traffic, quality of en-route WiFi access points, and potholes on the road. Micro-Blog [6] is an architecture which allows users to share multimedia blogs enhanced with inputs from other physical sensors of the mobile phone. However, the randomness of user movements and behaviors may bring difficulty in guaranteeing satisfactory coverage and sensing quality in the network. The quality of sensing data resulted by human may differ from one to another, which may not always satisfy the requirement of the applications. Compared with the dynamic nature of participatory sensing campaigns, wireless sensor networks are relatively stable. In most applications, after the WSNs are deployed, the topologies remain almost the same and their behaviors are more predictable. Although there are some random or unpredictable factors, such as damage of sensors, running out of energy, and data inaccuracy during transmission, their performance can be analyzed. It is obvious that the different natures and characteristics of stationary sensors and mobile phones could complement each other to perform collaborative sensing to reduce the deployment cost and provide satisfactory quality of sensing data.

In this paper, we consider a novel collaborative sensing paradigm which includes stationary sensors and mobile phones. Inspired by the mobile sensing architectures in [2,3], we investigate how stationary sensors could be deployed to complement the sensing performance of the mobile phones. In particular, we aim at providing collaborative sensing by both mobile phone participants and stationary sensors at satisfactory sensing quality and availability with a minimized deployment cost. We face some unique challenges when designing cost-effective and efficient sensing for this innovative collaboration paradigm. First, the existing wireless communication standard of sensors and mobile phones are different. Most of the existing sensors only support IEEE 802.15.4 standard and Zigbee for communication. On the other hand, mobile phones support mainly IEEE 802.11b/g standard (WiFi) and bluetooth, but not IEEE 802.15.4 and Zigbee. These limitations should be taken into account when building an integrated network. Second, the efficiency of the collaborative sensing paradigm depends on the sensing quality and the availability of mobile phone participants and sensors. Unfortunately, human behaviors and mobility may vary from time to time and they are not always predictable. Third, we would like to reduce the cost of the collaborative sensing system by minimizing the number of sensors required in the field, while guaranteeing the sensing quality and availability in long period of time. Moreover, one-time deployment is preferred to avoid extra costs and inconvenience caused by re-deployments.

To address these challenges, we propose a novel integration framework that incorporates mobile phones and wireless sensors seamlessly to provide cost-efficient collaborative sensing with high quality and availability at a minimized deployment cost. First, we present a new network architecture that support mobile phones and wireless sensors with different wireless communication standards. Considering the most common technologies on existing phones and sensors, we suggest a network with WiFi as backbone and overlayed with a IEEE 802.15.4 network for connecting to the sensors. Second, we introduce two mathematical models to estimate the sensing quality and mobility of mobile phone participants based on reputation statistics and probability model for mobility respectively. Third, we propose a cost-effective sensor deployment algorithm which minimizes the number of stationary sensors, while guaranteeing the sensing field are covered with the required sensing quality and probability in most of the time. Despite the dynamic behaviors of mobile phone participants, we aim at one-time deployment of wireless sensors to avoid unnecessary re-deployments for a practical and cost-effective solution. Forth, we evaluate our collaborative sensing paradigm comprehensively with real mobile traces from the mobile phone participants in Disney World (Orlando).

The remainder of this paper is organized as follows: Section 2 presents related work. In Section 3, we describe the system architecture for collaborative sensing with wireless sensors and mobile phone. In Section 4, we present our sensing and terrain models followed by the sensor deployment problem in the proposed paradigm. The sensor deployment framework for collaborative sensing in mobile phone assisted environment is presented in Section 5, together with detailed descriptions of the three modules. In Sections 6 and 7, we conduct extensive simulations to evaluate our framework and provide a case study based on real mobile traces. Finally, we conclude the paper in Section 8.

2. Related work

Participatory sensing has been studied recently to provide mobile phone-based data gathering [2]. It is coordinated across a potentially large number of participants over wide spans of space and time. Research topics on participatory sensing spread over privacy mechanisms, context-annotated mobility profiles for recruitment, performance evaluation for feedback, incentives and recruitment, etc. Applications of participatory sensing include, collecting and sharing information about urban air pollution [7], noise pollution [8], and consumer pricing information [9]. BikeNet [10] has successfully demonstrated a prototype that integrates a mobile personal sensor with multiple static sensors embedded in a homogenous environment. It utilizes an opportunistic networking paradigm, whereby mobile sensing platforms are tasked and data is muled or uploaded according to the opportunities that arise as a result of the uncontrolled mobility of the cyclists. Different from BikeNet, we consider stationary sensors and mobile phones that can connect to the Internet and share the same sensing duties, i.e. noise sensors and camera that are equipped on both type of devices. We work on the deployment problem of the stationary sensors to reduce the deployment cost and improve the sensing performance. Reddy et al. proposed a model for evaluating participation and performance in participatory sensing based on beta distribution [11]. They also proposed a recruitment engine that uses campaign specifications provided by an organizer to select a limited set of potential volunteers based on participants' previously gathered mobility profiles [12]. Their work focuses on the recruitment of mobile phone participants considering their geographic and temporal availability, while our framework works on the deployment problem of stationary sensors for collaborative sensing with mobile phone participants.

Opportunistic networks [13] and delay tolerant networks (DTNs) [14] have been proposed, which are driven by the popularity of mobile phones and personal electronic devices. Messages are routed through any possible node opportunistically as next hop, provided that it is likely to bring the message closer to the final destination. A number of routing and forwarding protocols have been proposed for opportunistic networks and delay tolerant networks (DTN) [15,16]. Burns et al. [17] proposed the MV routing protocol which learns the movement pattern of network participants and uses it to enable informed message passing. A similar approach is followed in the PROPHET protocol [18] to improve the delivery rate. Zhao et al. [19] proposed a *message ferrying* approach to address the network partition problem in sparse ad hoc networks. These work focus on the communication and information sharing between intermediate peers opportunistically. Different from them, our work provides an infrastructure of WSNs, but using mobile phones as complementary tools to collect sensing data collaboratively. We aim at providing optimal deployment of wireless sensors to minimize the system cost, while guaranteeing enough sensing quality and availability by considering the mobility and sensing quality of mobile phone users.

Techniques for improving the performance of uncontrolled mobility opportunistic sensor networking (OSN) has been studied in [20,21]. While this novel OSN approach can allow large scale sensing at a lower cost compared to an ubiquitous static infrastructure of sensing devices, the opportunistic nature of sensing and communication presents challenges to the fundamental sensor networking operations. Eisenman et al. [20] proposed sensor sharing and sensor substitution as two techniques for mobile sensors to improve the probability of successfully and more expediently completing the sensing tasks. They further improved the sensing quality of participants in the context of sensor sharing in [21]. They investigated on the MetroSense architecture for large scale sensing based on human-carried (mobile) sensors, leveraging opportunistic interactions between sensors, to get large scale coverage of human-centric activity and environment. They studied comprehensively on opportunistic sensing and data collection for human-centric applications. Different from an opportunistic approach, we consider a system architecture with infrastructure for reporting data from both the stationary sensors and mobile phones. We focus on the deployment problem of the stationary sensors to provide satisfactory sensing performance of the system considering the uncontrolled mobility of the mobile phones.

Deployment problems in traditional wireless sensor networks have been widely studied. Tian et al. proposed a node-scheduling scheme to reduce system overall energy consumption and increase system lifetime [22]. Their scheme turns off some redundant nodes and guarantees that the original sensing coverage is maintained. Dhillon and Charkrabarty proposed two greedy algorithms for deployment of wireless sensor network [23]. They built a probability model for wireless sensors based on a grid sensing field. Chakrabarty et al. proposed a deployment strategy to reduce cost for wireless sensor network which has different kind of wireless sensors [24]. They formulated the problem with integer linear programming. Poduri and Sukhatme proposed an algorithm based on artificial potential fields for the self-deployment of a mobile sensor network [25]. Their deployment strategy is researched in a network with the constraint that each of the nodes has at least K neighbors. Our work is different from the above as we consider sensor deployment in mobile phone assisted environment. We investigate how sensor deployment can be optimized cost-effectively considering the mobility and human behaviors in mobile phone sensing. Our framework enables stationary sensors and mobile phone participants complement each other to provide satisfactory sensing services with minimized cost. Although sensor coverage with mobile sensors have been investigated, but most of them focus on deploying or controlling the mobility of mobile sensors. For instance, Gupta et al. [26] proposed a stochastic sensor movement strategy that uses a small number of mobile sensors to monitor various threats in a geographical area. Similarly, Wang et al. [27] designed two bidding protocols to guide the movement of mobile sensors to cover the coverage holes of the static sensors. Different from their work, we consider mobile phones with uncontrolled mobility as the mobile sensors. Under this uncontrolled mobility scenario, our work aims at improving the sensing performance by deploying stationary sensors at optimal locations.

3. Collaboration sensing paradigm with wireless sensors and mobile phones

We aim at designing a novel collaborative sensing paradigm that connects wireless sensors and mobile phones in a network, such that users can collect and process data from both of them.

3.1. System architecture

The network in our paradigm includes both wireless sensors and mobile phones. Unfortunately, the different wireless communication standards on mobile phones and wireless sensors hinder direct communications between them. Most of the existing wireless sensors communicate with IEEE 802.15.4/ZigBee standard [28]. Although we can find sensors that support WiFi [29] and bluetooth [30], they are not very common. On the other hand, most of the mobile phones are equipped with GPRS, WiFi, bluetooth and infra-red nowadays [6], but they are rarely Zigbee enabled [31]. We need a new network architecture that support devices with different communication standards to collect and integrate data from them. We explored different implementations which enable mobile phones communicating with wireless sensors. For example, we can install a wireless access point like Asus WL-500GP [32] which supports IEEE 802.11b/g and is equipped with USB ports for connecting to the sensors. Alternatively, we can connect a mobile phone such as Nokia N810 [33] through its USB port or a IEEE 802.15.4/ZigBee USB adapter [34] to the sensors.

Although USB ports and adapters could be used to connect mobile phones and sensors, they are far from a convenient and practical solution to the general mobile phone participants. Based on the most popular existing technology, we suggest a hybrid network architecture as shown in Fig. 1 for our collaborative sensing paradigm. The proposed architecture supports sensors and mobile phones equipped with either IEEE 802.15.4/ZigBee or IEEE 802.11b/g standards. Given the popularity and wide coverage of WiFi, we consider WiFi as the backbone of our network which allows mobile phone users to report their data easily and freely. In the meantime, we also deploy a sensor network that enables multi-hop communication with IEEE 802.15.4/ZigBee among the wireless sensors. The sensor network includes one or multiple sink nodes that support IEEE 802.11b/g to overlay the sensor network with the backbone network. We may also include a gateway server to process and store the data collected by the sensors and mobile phones. We do not require necessary interactions between sensors and mobile phones in this stage to keep our design simple and practical.

3.2. Collaborative sensing with sensors and mobile phones

The network can be deployed in different places to monitor the environment and human activities. Potential sensing environments include amusement parks, universities, tourist attractions, etc. Fig. 2 shows the map of an amusement park where a number of games, theaters and aquariums are located at different zones. The smiley faces in the figure indicate the spots that many people like to go. The map also shows some green areas with trees and possibly mountains that attract less people. We intend to build a network for the administrator to monitor and collect data from the environment considering the unique behaviors and mobility of the mobile phone participants collaborating with wireless sensors.

We observe that the wireless sensors and mobile phones have different properties, such as mobility,

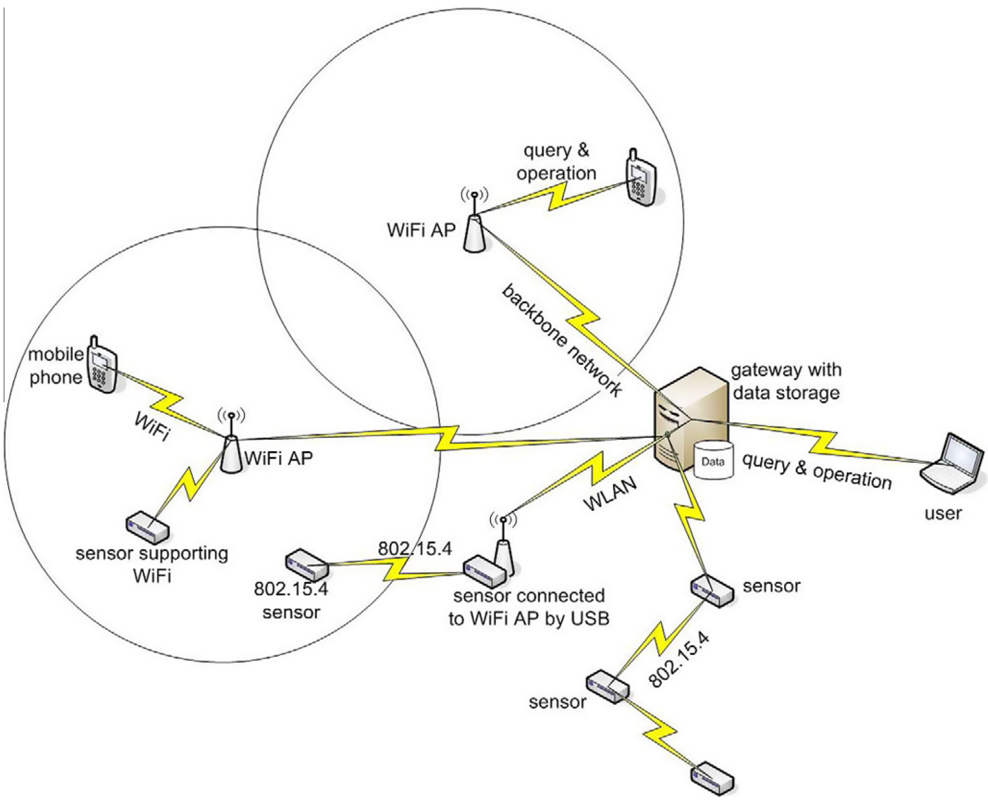

Fig. 1. System architecture.

Fig. 2. Map of amusement park where smiley faces indicate the crowds.

Table 1
Comparisons between wireless sensors and mobile phones.

Properties	Wireless sensors	Smart phones
Wireless interfaces	IEEE 802.15.4, bluetooth	Bluetooth, GPRS, WiFi
Mobility	Stationary	Mobile
Batteries	2 AA batteries, rarely recharged	Proprietary, regularly recharged by users
Processor	7.37 MHz (MICA2) [35]	Around 1000 MHz (ARM Cortex) [36]
Memory	512 kB Flash (MICA2) [35]	Around 2 GB SD card
Sensing capabilities	Wide variety (e.g. temperature, humidity, noise, pressure, gas)	Mainly GPS, sound, images, motions

computation power and sensing capabilities (see Table 1). These are also the reasons making them complementary to each other in a sensing system. We consider some primary sensing data like the noise level and images to be collected by the microphone and the camera of the sensors or mobile phones. Based on the capability of the sensors and phones, other secondary data like temperature, pressure and motion could also be detected with different types of sensing components in the sensors or the mobile phones. We focus on the primary data which could be collected by sensors or mobile phones interchangeably in this work. However, the approach could be extended easily for different kinds of sensing data and application requirements. Sensors could be deployed cost-effectively with the assistance of mobile phones for monitoring the environment.

4. The sensor placement problem in sensor-mobile phone collaboration paradigm

4.1. Sensing and terrain models

In our collaborative sensing environment, there are two types of devices: mobile phones and wireless sensors. Since participants may have different kinds of mobile phones, their sensing capabilities differ from one to another. We extend the model proposed by Dhillon and Charkrabarty for the detection probability of a target by a sensor in a terrain of sensing area [23]. We assume that the detection probability varies exponentially with the distance between the target and the sensor. A target at distance h from a sensor is detected by that sensor with probability

$$z(h) = \sigma_t e^{-\epsilon h},$$

where ϵ can be set to different values to model the sensing quality of heterogeneous sensors and the rates at which their detection probability diminishes with distance. σ_t can model the degradation on sensing quality of individual sensors at different time t in a changing environment. The choice of a sensor detection model could be changed according to different sensing environments without affecting our algorithm. Terrain is an important factor in wireless sensor networks, which heavily affects the sensing capabilities of the sensing devices. For example, obstacles such as buildings can block the vision of some sensors. Fig. 3 shows an example of sensing field with obstacles.

In our paper, the sensing field is represented as a grid of two- or three-dimensional points g_i. The distance between adjacent grid points is d. For simplicity, we assume that sensors are deployed only at these grid points. The participants' sensing actions are also considered to be performed within these grids. The number of grid points in the

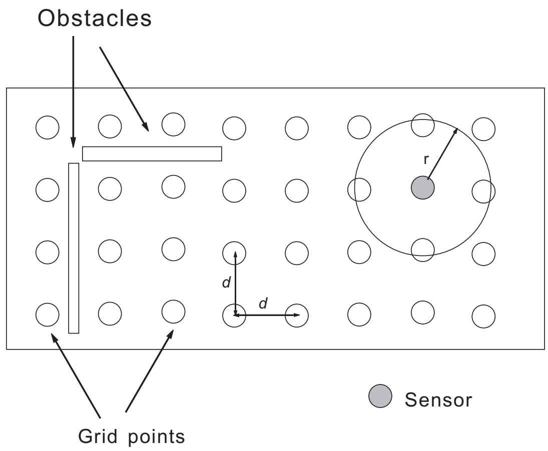

Fig. 3. Sensing field with obstacles.

sensing field is denoted by N. We define the detection probability matrix, D, which describes the detection probability from the sensors or mobile phones to the targets as

$$D = \begin{pmatrix} d_{1,1} & d_{1,2} & \cdots & d_{1,n} \\ d_{2,1} & d_{2,2} & \cdots & d_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n,1} & d_{n,2} & \cdots & d_{n,n} \end{pmatrix}$$

in which $d_{i,j}$ indicates the sensing probability of a target in grid point j by a sensor or mobile phone in grid point i. The probability matrix can be calculated according to our knowledge of the sensing and terrain models. We let $dis(i,j)$ denote the distance from grid point i to grid point j. Then, entries of D are calculated as follows

$$d_{i,j} = \begin{cases} z(dis(i,j)) & \text{if vision from } i \text{ to } j \text{ is not blocked}, \\ 0 & \text{otherwise}. \end{cases}$$

The detection probability matrix depends on the sensing capability of the sensors and mobile phones, so it may vary from one type of devices to another even though they are monitoring the same terrain. Given that our framework is module-based, it is easy to extend to include more advanced sensing models. For instance, the sensing context of changing environment could be considered in terms of the data quality at different location and time [37]. Alternative sensing models could be applied in our framework depending on the application requirements. Since we aim at one-time deployment for the stationary sensors, Q_{req} and P_{req} could be set more strictly and act as upper bound requirements of the designed application.

4.2. Problem description

Many factors have to be considered when a wireless sensor network is deployed, such as energy consumption, connectivity and deployment cost. In a sensing environment with sensors and mobile phones, the deployment cost of sensors could be relatively expensive in comparison with the recruitment of mobile phone participants. Minimizing the number of sensors in deployment could definitely reduce the cost for the sensing applications. Our aim is to deploy minimum number of sensors and provide enough coverage and sensing quality for every grid point in the sensing field.

The grid points in a sensing area may have different importance according to the application requirements. For example, some grids are critical to the sensing campaign where data need to be sensed with higher priority. Such importance can also be changed during the progress of participatory sensing from period to period. Thus every grid point g_i is associated with a pair $\langle Q_i, P_i \rangle$, where Q_i indicates the lowest quality of data required by the campaign expressed as a real number in the range of $[0,1]$. The quality of sensing result could be judged by the organizers or experts. The parameter P_i indicates the lowest required coverage probability for that grid point. Regarding to the coverage probability, we mean the probability that a grid point g_i is sensed by any mobile phone participants or wireless sensors. At the beginning of each period, the quality and probability vectors $\mathbf{Q_{req}} = (Q_1 Q_2 \cdots Q_N)$ and $\mathbf{P_{req}} = (P_1 P_2 \cdots P_N)$ are given as input parameters.

Wireless sensor network should complement mobile phone participants in sensing to make sure that enough sensing quality and availability could be achieved. Our sensor deployment algorithm should be adaptive to human actions. It is not wise to deploy the network once and then remain it the same during the whole campaign. The participatory sensing campaign can be divided into several periods. Before each period, the wireless sensor network could be reconfigured slightly according to the information from the participatory sensing campaign and the behaviors of its participants. However, re-deployments are unfavored due to the extra time, effort and cost. In case that re-deployment is not possible, our scheme could predict the behavior of the mobile phone participants and figure out an optimal sensor deployment that guarantees the best sensing quality at most of the time in the future.

5. Wireless sensor deployment in mobile phone assisted environment

We propose a seamless integrated framework for the deployment of wireless sensors in mobile phone assisted environment. Our framework consists of three modules, which communicate with each other by passing parameters (see Fig. 4). The implementation of every module can

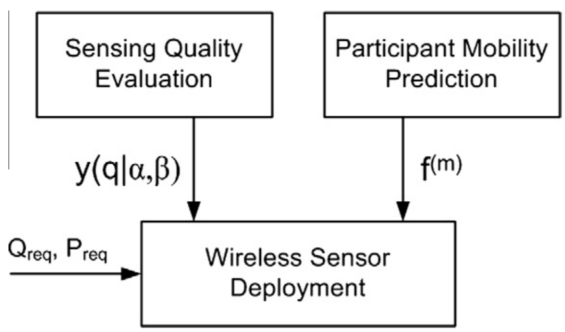

Fig. 4. Overview of our framework.

be replaced by another provided that the interfaces between the modules remain the same. This gives our deployment framework great flexibility and generality, which is important to support a diverse variety of participatory campaigns.

This section is organized as follows: firstly, we describe the sensing quality evaluation model. Then, we explain the mobility prediction model for the participants. Finally, we use the above two models to figure out the locations that require the deployment of extra wireless sensors.

5.1. Evaluation of sensing quality of participants

The sensing quality of participants are affected by many human factors, like community expertise [38], trustworthiness of the participants, data quality of their mobile phones, etc. Some participants will report their data reliably and honestly which can provide the system high sensing quality that satisfy the application requirements, while some bad participants might not always provide useful data. Participatory sensing reputation metrics can incorporate expertise, data quality, credibility and certainty among the participants [11].

Evaluating sensing quality of participants has an inherent relation with reputation evaluation of transaction parties in e-commerce [39]. Online markets require a great deal of trust among trading partners to mitigate the risks involved in anonymous transactions. In reputation systems for e-commerce, the reputation of merchants are calculated according to the feedbacks and remarks from customers [40]. Similarly, in participatory sensing, the participants may act as merchants who sell goods and the organizers or experts may act as the customers. Unlike peer-reviews in on-line market, the organizers in participatory sensing can evaluate performance of the participants by comparing the sensing data among the participants and checking whether their collected data meet the application requirements.

Moreover, the sensing quality of participants depend heavily on the time and locations that their actions are performed. For instance, a mobile phone participant may be more willing to report data when he is traveling, rather than hurrying to work. A participant may gain more experiences gradually and report data with higher quality along time. One may even change to a new mobile phone with stronger sensing capabilities. The dynamic natures of human activities at different time and place bring unique challenges in sensing quality evaluation. We hence propose a mathematical model to estimate the sensing quality of mobile phone participants considering the order of their previous actions over time.

Beta distribution can be applied to model the performance of a participant, which is based on the statistics on probability distribution of some binary events [11,41]. The beta probability distribution function $y(q|\alpha,\beta)$ is expressed by

$$y(q|\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} q^{\alpha-1}(1-q)^{\beta-1},$$

where Γ is the Gamma function, $0 \leqslant q \leqslant 1$, α and β are integers greater than 0. The function is indexed by two parameters, α and β. Consider a process has two possible outcomes $\{x,\bar{x}\}$, r denotes the number of outcome x and s denotes the number of outcome $\bar{x}$. Then the probability density function of outcome x in the future is a beta distribution by setting $\alpha = r + 1$ and $\beta = s + 1$. At the beginning, α and β are initialized to be 1, which result in a uniform distribution.

The results of participants' performance can be represented as a stochastic process which has two possible outcomes $(x,\bar{x})$. x means a successful action and $\bar{x}$ means an unsuccessful action. For the ith outcome, we define random variables r_i and s_i as follows

$$r_i = \begin{cases} 1 & \text{if the } i\text{th action is successful}, \\ 0 & \text{otherwise}. \end{cases}$$

$$s_i = \begin{cases} 1 & \text{if the } i\text{th action is unsuccessful}, \\ 0 & \text{otherwise}. \end{cases}$$

Beta distribution can be applied to model participants performance by setting r as number of successful actions and s as number of unsuccessful actions, such that

$$r = \sum r_i, \quad s = \sum s_i.$$

As the campaign progresses, the sensing performance of the participant is changing. The more recent performances is more representative than the old ones, so that old performances should have less weights than recent ones. We introduce the following aging factor that emphasizes on the order of action results as

$$k_i = \lambda^{(t-t_i)},$$

where t is the current day and t_i is the day when the action is performed. Meanwhile, it has the advantage of being calculated recursively by

$$r = r'\lambda^{(t_i-t_{i-1})} + r_i, \quad s = s'\lambda^{(t_i-t_{i-1})} + s_i,$$

where r' and s' are the r and s in the previous time stamp at t_{i-1}.

In practical campaign, the feedbacks from organizers about the participants are not simply binary because the result of an action cannot be only judged as successful or unsuccessful. In this case, the organizers may give the feedback in form of a pair of real numbers $\langle r_i,s_i\rangle$, where r_i indicates the satisfaction degree and s_i indicates the dissatisfaction degree. In addition, it is also possible for the organizers to give the feedback by only one real number v_i. Then, r_i and s_i can be calculated by

$$r_i = \frac{1+v_i}{2}, \quad s_i = \frac{1-v_i}{2}.$$

Since different tasks may have special difficulties, it is straightforward that a positive weight w_i can be applied to show the levels of difficulty. More important the task is, the larger its weight is. Then, r_i and s_i can be calculated by

$$r_i = \frac{w_i(1+v_i)}{2}, \quad s_i = \frac{w_i(1-v_i)}{2}.$$

Together with the aging factor, the parameters α and β can be calculated as follows

$$\alpha = 1 + \sum r_i = 1 + \sum \frac{w_i(1+v_i)}{2}\lambda^{(t-t_i)},$$
$$\beta = 1 + \sum s_i = 1 + \sum \frac{w_i(1-v_i)}{2}\lambda^{(t-t_i)}.$$

After that, we can obtain the probability that the next sensing action of a participant whose result is better than Q by calculating $\int_Q^1 y(q|(\alpha,\beta))\mathrm{d}q$. Note that our framework is extendable to include more advanced sensing quality estimation models that consider the sensing context and dynamic application requirements in changing environment.

5.2. Prediction of participant mobility

Another dynamical aspects of participants are their motions because nobody knows what exactly they will do tomorrow. However, their motions are not completely random as most people have their schedule everyday or places they used to go. For example, students usually go to the university canteen for lunch after their morning lectures. Similarly, tourists who just played with the roller coaster in the amusement park are likely to play with the ferris wheel nearby. The motion patterns of human beings could be learned and predicted by some mathematical models. We formulate and predict participants' behaviors by the Markov model here which requires only the sensing data uploaded by the participants.

Since most people care about their privacy, a reliable way to collect information of users' motions is using their uploaded geo-tagged data from which the locations can be obtained. Their motions in a day can be described by a sequence L. Fig. 5 shows an example of motion sequence represented as $L = [A,D,C,E,B]$. Every element in the sequence describes the location where the task is performed. The sequence of participants' motions can be modeled by a Markov chain $\{c_1,c_2,\ldots,c_n\}$. Each state c_i corresponds to the grid point g_i in the sensing field.

According to the property of Markov transition matrix Y, $p_{i,j}^{(n)}$ gives the probability that the Markov chain, starting in state c_i, will be in state c_j after n steps. We calculate the probability for the starting states $\mathbf{f}^{(0)} = \left(f_1^{(0)} f_2^{(0)} \cdots f_n^{(0)}\right)$ of the participants in a period T, which can be obtained by some statistics from the previous participants' actions.

$$Y = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,n} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,n} \\ \vdots & \ddots & \vdots & \\ p_{n,1} & p_{n,2} & \cdots & p_{n,n} \end{pmatrix}.$$

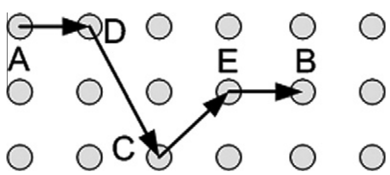

Fig. 5. Example of participant motions.

Let $f_i^{(m)}$ denote the probability that a participant is in state c_i at time m. These state probability at time m are conveniently arranged in a row-vector

$$\mathbf{f}^{(\mathbf{m})} = \left(f_1^{(m)} f_2^{(m)} \cdots f_n^{(m)}\right)$$

known as the state probability vector at time m. It can be calculated by

$$\mathbf{f}^{(\mathbf{m})} = \mathbf{f}^{(\mathbf{m-1})} Y.$$

Repeated application of this recursive equation yields

$$\mathbf{f}^{(\mathbf{m})} = \mathbf{f}^{(\mathbf{0})} Y^m.$$

From the Markov transition matrix Y, we can calculate the probability of grid point g_i being visited by a participant during one day as

$$1 - \prod_{t=0}^{N_d}\left(1 - f_i^{(m)}\right),$$

where N_d is the number of time units in one day.

5.3. Cost-effective deployment of wireless sensors

Given the corresponding sensing requirement $\langle Q_i, P_i \rangle$ of each grid point g_i, the probability that its data can be sensed by any mobile phone participants with the required quality is obtained by Algorithm 1. For each grid point g_i, we calculate the probability Pr_i that g_i cannot be sensed by any participants x in a time period T. Then the probability Cov_i^T that g_i cannot be covered by any participants is $\prod_{\forall x} Pr_i$. Finally, $Cov_i^T = 1 - \prod_{\forall x} Pr_i$ denotes the probability that g_i can be covered by the mobile phone participants, where $i = 1\ldots N$ with N is the number of grids in the monitored area.

Algorithm 1. Calculation of coverage for each grid point

```
for all g_i is a grid point do
  Pr_i = 1;
  for all x is a participant do
    p_x = ∫_{Q_i}^1 y_x(q|α, β)dq;
    for all g_j is a grid point do
      if d_{j,i} p_x > Q_req then
        Pr_i = Pr_i ∏_{t=0}^T (1 − f_j^(t));
      end if
    end for
  end for
  Cov_i^T = 1 − Pr_i;
end for
```

We can obtain the coverage probability $\mathbf{Cov}^{\mathbf{T_1}}$, $\mathbf{Cov}^{\mathbf{T_1}},\ldots,\mathbf{Cov}^{\mathbf{T_n}}$ at each grid in different periods of time $T_1, T_2, \ldots, T_n$, where $\mathbf{Cov}^{\mathbf{T_j}} = \left(Cov_1^{T_j} Cov_2^{T_j} \cdots Cov_N^{T_j}\right)$. Since one-time deployment is often required for sensor networks, we summarize the average coverage probability, $\overline{\mathbf{Cov}}$, by taking an average of $\mathbf{Cov}^{\mathbf{T_j}}$ over different periods as

$$\overline{\mathbf{Cov}} = \sum_{j=1}^{n} \mathbf{Cov}^{\mathbf{T_j}}/n.$$

Given the required coverage probability $\mathbf{P_{req}}$ for the grids, we can calculate the missing coverage probability vector $\mathbf{M} = \mathbf{P_{req}} - \overline{\mathbf{Cov}}$, where $\mathbf{M} = (M_1 M_2 \cdots M_n)$. The grid cells with $M_i > 0$ need to be covered by extra wireless sensors with the required sensing quality Q_{req}. We represent these set of grid cells and model their wireless sensor deployment as a set-covering problem. The required sensing quality Q_{req} is quantified as the number of elements to be covered for each of these grid cells. The elements of all these grid cells are denoted as X, where $X = \cup\{Q_i | M_i > 0, \forall i\}$. In other words, X contains all elements that need to be covered in the grids with missing coverage, i.e. $M_i > 0$. The set-covering problem has been proven as a NP-hard problem and heuristic algorithms have been suggested for solving related problems in sensor networks [23,42].

An instance (X, F) of the set-covering problem consists of a finite set X and a set F of subsets of X. We assume that each element in X appears in at least one of the subsets in F,

$$X = \cup_{S_i \in F} S_i,$$

where each S_i represents the elements that can be covered by a sensor deployed at grid cell g_i, $S_i = \cup_{\forall j} d_{i,j}$ and $d_{i,j}$ are the elements referring to the quantified sensing quality from grid cell g_i to g_j by a stationary sensor.

The set-covering problem here requires us to determine a minimum sized subset of F that covers all the elements of X. In other words, given an instance (X, F), we are required to find a set $C \subseteq F$ such that

$$X = \cup_{S_i \in C} S_i \quad \text{and} \quad C \text{ is minimal}.$$

A greedy algorithm for sensor deployment is presented in Algorithm 2. The algorithm maintains a set of elements of X that are yet uncovered in U. In each iteration of the while loop, the algorithm calculates the cost effectiveness, $\gamma = \frac{c(S_i)}{|S_i \cap C|}$ for each S_i. It greedily chooses the set S_{i*} that has the minimum γ, until all of the elements of X are covered or there is no available sensors. The set C contains all the sets that have been chosen as part of the set cover at any point during the operation of the algorithm.

Algorithm 2. Deployment of wireless sensors

Input: (X, F)
Sensors_num = Sensors_max;
$U \leftarrow X$;
$C \leftarrow \phi$;
while $(U \neq \phi)$ and (Sensors_num > 0) **do**
  $\gamma = \frac{c(S_i)}{|S_i \cap C|}$;
  select the S_{i*} with the smallest γ;
  For each $e \in S_i - C$, set $price(e) = \gamma$;
  $U \leftarrow U - S_{i*}$;
  $C \leftarrow C \cup S_{i*}$;
  Sensors_num = Sensors_num-1;
end while
return C;

Theorem. *The above greedy algorithm is an H_u factor approximation algorithm for the minimum set cover problem, where $H_u = 1 + \frac{1}{2} + \cdots + \frac{1}{u} \approx \log u$, where u is the total number of elements in X.* [42]

Proof. We know $\sum_{e \in U} price(e)$ = cost of the greedy algorithm = $c(S_1) + c(S_2) + \cdots + c(S_m)$ because of the nature in which we distribute costs of elements.

Consider the optimal sets are $O_1, O_2, \ldots, O_p$, such that

$$OPT = c(O_1) + c(O_2) + \cdots + c(O_p). \tag{1}$$

Now, assume that the greedy algorithm has covered the elements in C so far. Then, we know that uncovered elements, or $|U - C|$, are at most the intersection of all of the optimal sets intersected with the uncovered elements:

$$|U - C| \leqslant |O_1 \cap (U - C)| + |O_2 \cap (U - C)| + \cdots + |O_p \cap (U - C)|. \tag{2}$$

In the greedy algorithm, we select a set with cost effectiveness γ, where

$$\gamma \leqslant \frac{c(O_i)}{|O_i \cap (U - C)|},$$

such that,

$$c(O_i) \geqslant \gamma |O_i \cap (U - C)|, \tag{3}$$

where $i = 1 \ldots p$. We know this because the greedy algorithm will always choose the set with the smallest cost effectiveness, which will either be smaller than or equal to a set that the optimal algorithm chooses. Given Eqs. (1) and (3), we have

$$OPT = \sum_i c(O_i) \geqslant \gamma \sum_i |O_i \cap (U - C)|.$$

Applying Eq. (2), we obtain

$$OPT \geqslant \gamma |U - C|.$$

Then,

$$\gamma \leqslant \frac{OPT}{|U - C|}.$$

Therefore, the price of the kth element is

$$\gamma \leqslant \frac{OPT}{u - (k - 1)} = \frac{OPT}{u - k + 1}.$$

Finally, we get the total cost of the set cover is bounded by

$$\sum_{k=1}^{u} price(e_k) \leqslant \sum_{k=1}^{u} \frac{OPT}{u - k + 1} = OPT\left(1 + \frac{1}{2} + \cdots + \frac{1}{u}\right) = OPT \cdot H_u. \qquad \square$$

6. Performance evaluations

We evaluate the performance of our framework by simulating a sensing field of 10×10 grid points with randomly generated obstacles in the environment. The distance between adjacent grid points is 1 unit. Each grid point has a required coverage probability. Their required lowest sensing quality lies uniformly random in the range of $[0.6, 1]$. In our simulations, the mobile phones and wireless sensors share the same detection probability function as

$$z(h) = e^{-0.4h}.$$

6.1. Deployment allows reconfigurations

In the first experiment, we consider a sensing campaign with 3 mobile phone participants. A sensing campaign is a sensing activity or sensing application designed to collect sensing data for a specific purpose. The term is also used in participatory sensing, which represent a sensing application or a sensing activity that is supported by a number of mobile phone users [2,43]. The whole campaign lasts for 200 days which are divided into 10 periods. Re-deployment is allowed at the beginning of each period simply to study the necessary deployment changes in optimal solution. We set all grid points with the same required coverage probability of 0.9 in this experiment. We impose some motion patterns to the participants. The sensing field is divided into 4 small areas and each of them contains 5×5 grid points. Each participant only performs sensing in their own small area out of the four. Three out of these four areas have participants moving around with random motion. The remaining one is simulated as a lake, where the participants cannot go there.

Fig. 6 compares the coverage for the network with and without sensors deployed. We show the coverage satisfaction percentage in our figure, which means the percentage of grids that can satisfy the required coverage probability which is 0.9 here. Coverage satisfaction percentage is an index showing the satisfaction level on coverage in sensing. In our algorithm, the sensors are deployed after the first period, such that our framework can get enough information about the participants. From the figure, we see that only around 30% of the grids can achieve the required coverage probability on average. On the other hand, about 80% of the grids on average can achieve the required coverage probability in the network with sensors deployed. Fig. 7 shows the number of sensors deployed in the campaign. The number of sensors required is around 18–20 in this case. It is surprising that re-deployments are not required so often under random motion of participants in divided areas.

This experiment is repeated by setting a lower required coverage of 0.6. Again, Fig. 8 compares the coverage satisfaction percentage of a network with and without deployed sensors. It shows that the coverage satisfaction percentage becomes higher when the required coverage probability decreases. Fig. 9 shows that the corresponding number of sensors deployed decreases in compare with Fig. 7.

6.2. One-time deployment

In this experiment, we evaluate the performance of our framework considering one-time sensor deployment without any reconfiguration. The experimental setting here is the same as the first experiment with the required coverage probability at 0.9. The wireless sensor network is deployed only once after our framework has learned enough information in the first period. We show the coverage satisfaction percentage after 18 sensors are deployed in Fig. 10. The figure shows that our proposed sensor deployment algorithm can achieve much better coverage satisfaction percentage than the random deployment algorithm. The coverage satisfaction probability of random

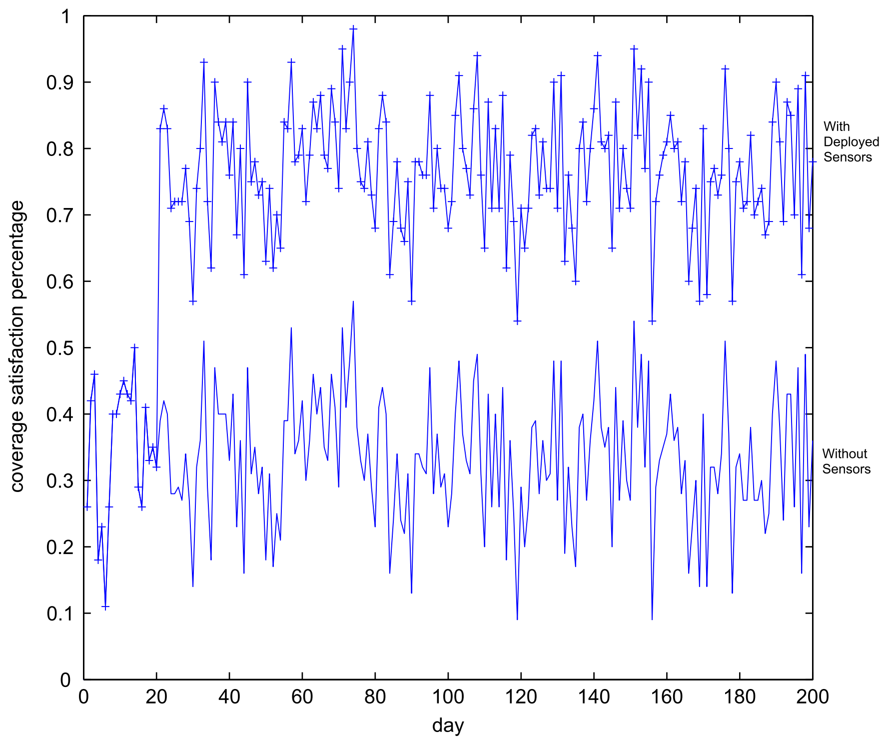

Fig. 6. Comparison on coverage satisfaction percentage with required coverage of 0.9.

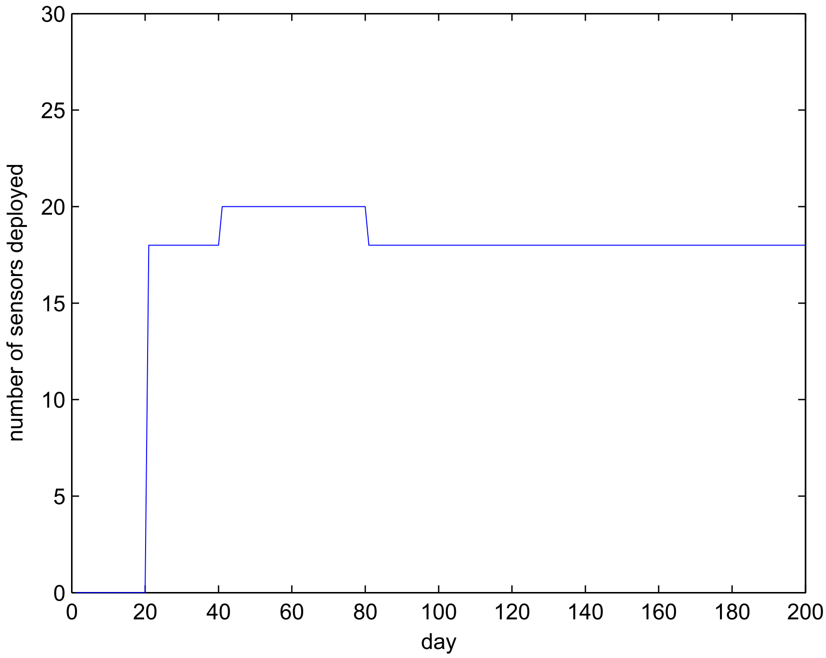

Fig. 7. Number of sensors deployed with required coverage of 0.9.

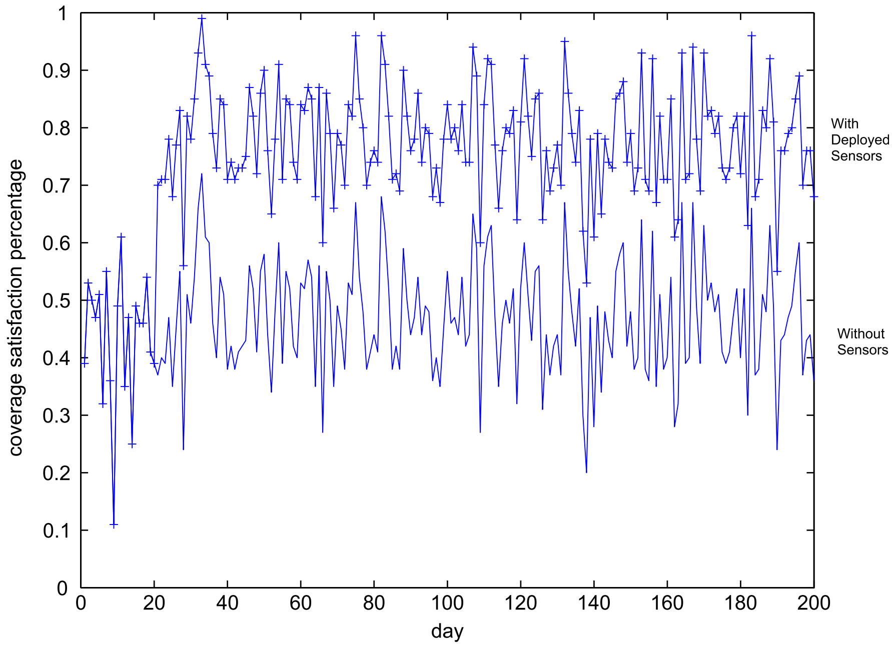

Fig. 8. Comparison on coverage satisfaction percentage with required coverage of 0.6.

deployment with equal number of sensors is also plotted for comparison. Both our algorithm and the random deployment algorithm can achieve better coverage than sensing with only mobile phone participants. The results demonstrate that wireless sensors can complement the mobile phone participants to improve the coverage.

7. A case study with mobile traces

We further evaluate our sensor deployment with real mobile traces collected by the mobile phone participants in Disney World (Orlando) [44,45]. The human mobility traces are collected with GPS receivers carried by 41

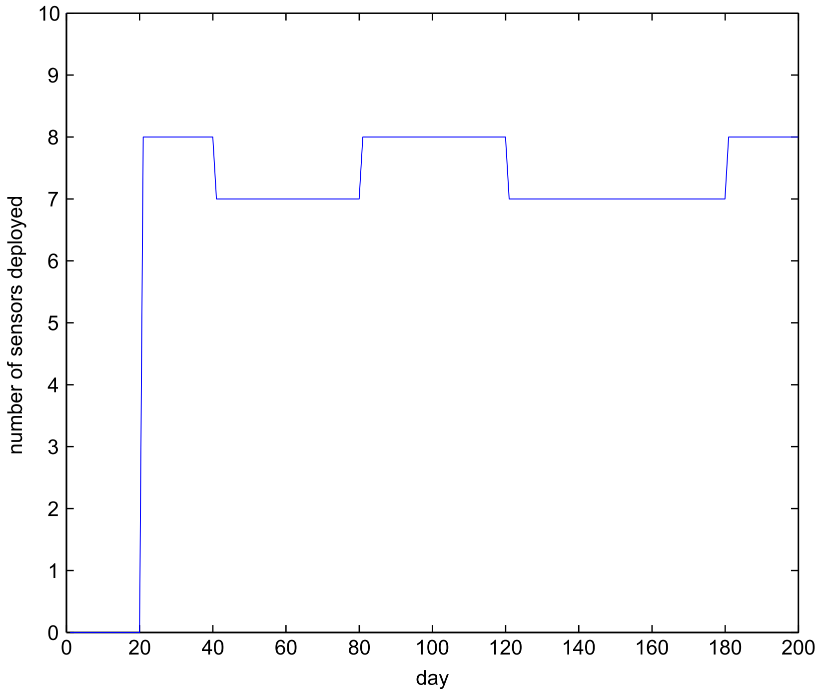

Fig. 9. Number of sensors deployed with required coverage of 0.6.

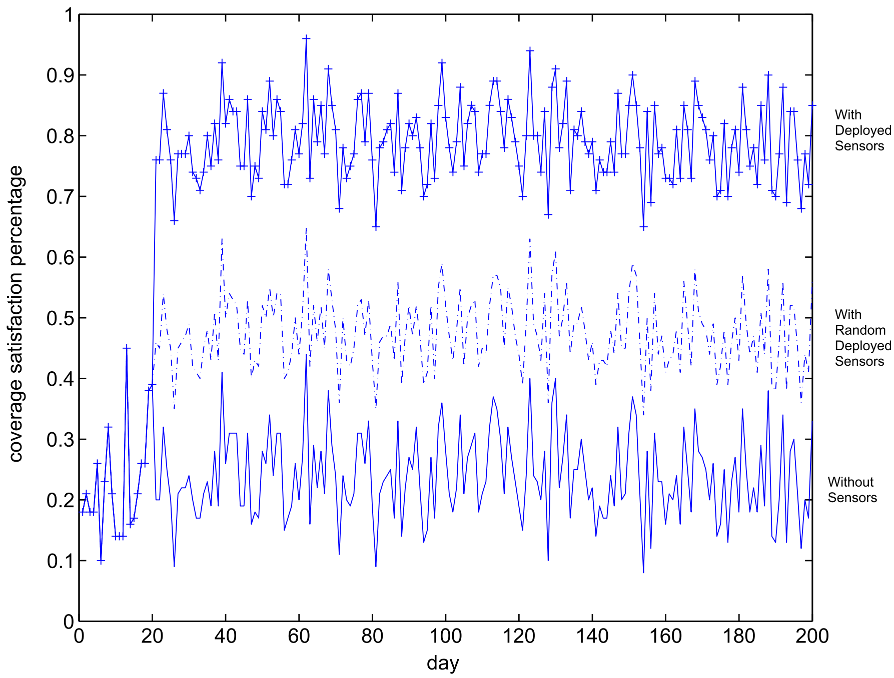

Fig. 10. Comparison on coverage satisfaction percentage with one-time deployment.

participants at every 10 s. These traces are mapped into a two dimensional area and recomputed to a position at every 30 s by averaging three samples over that 30 s period to account for GPS errors [44].

We monitor a 1 km $\times$ 1 km area at the center of the theme park with our framework considering the mobile traces of 10 h. The sensing area is divided into 10 $\times$ 10 grid cells with the grid points located at the center of each of them. We assume that the mobile phones and wireless sensors share the same sensing quality. A mobile phone or a sensor located in a grid can provide full sensing quality within that grid. The sensing quality degrades to only 50% in the neighboring grids and only 15% two grids away. The sensing quality drops to 0% for grids further away. The

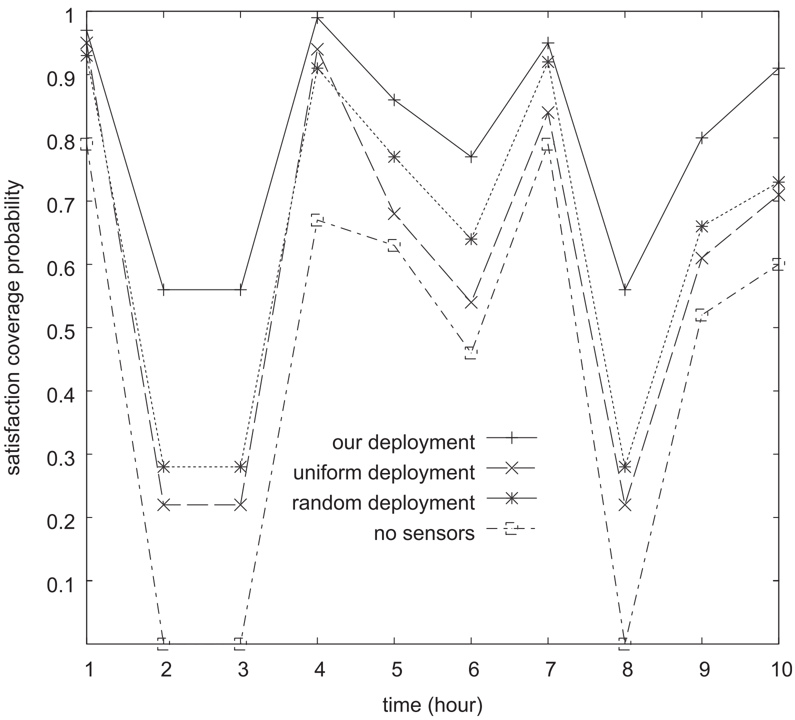

Fig. 11. Coverage satisfaction probability with one-time deployment at P_{req} = 0.5 and Q_{req} = 0.5.

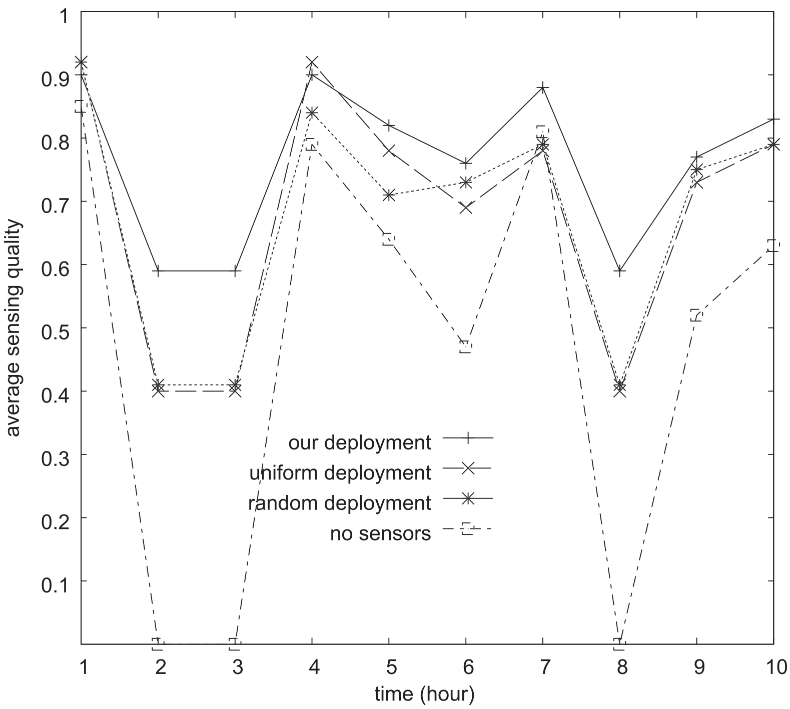

Fig. 12. Average sensing quality with one-time deployment at P_{req} = 0.5 and Q_{req} = 0.5.

sensing data from mobile phones and sensors to the same grid could complement each other to achieve higher sensing quality. We set the expected coverage probability P_{req} and the expected sensing quality Q_{req} for all grids in this experiment. We consider one hour as a time unit for a grid to be monitored by mobile phones and/or sensors with P_{req}

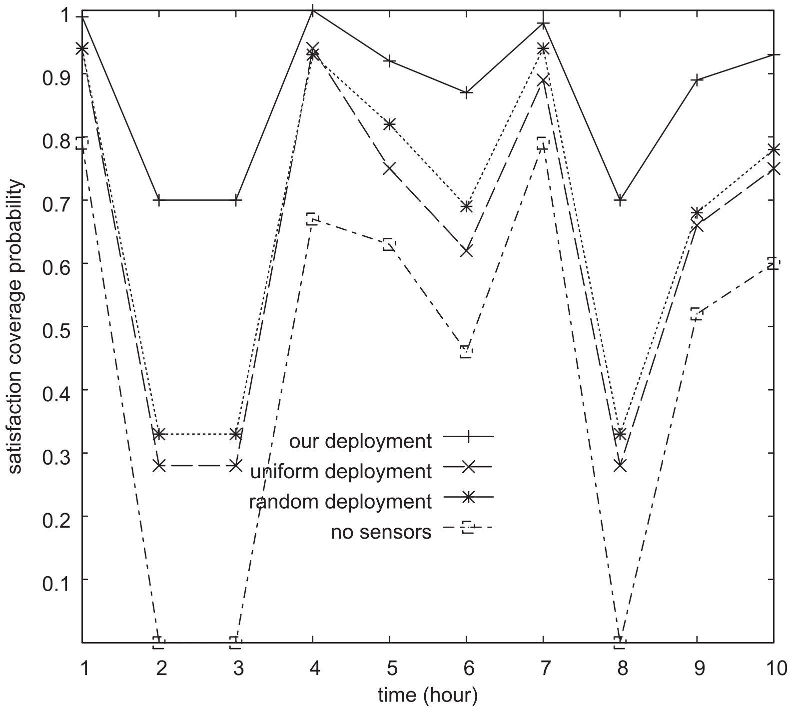

Fig. 13. Coverage satisfaction probability with one-time deployment at $P_{req} = 0.7$ and $Q_{req} = 0.7$.

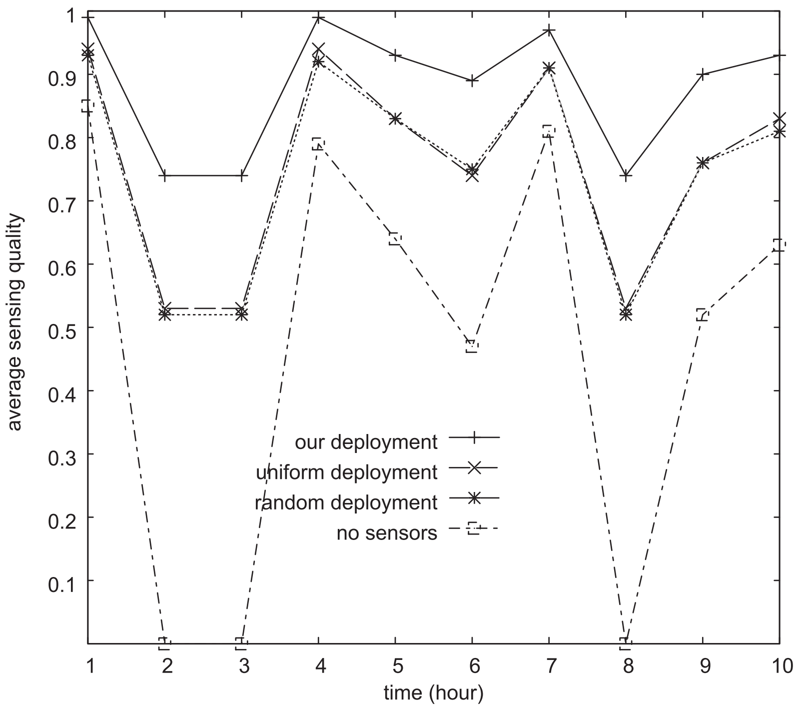

Fig. 14. Average sensing quality with one-time deployment at $P_{req} = 0.7$ and $Q_{req} = 0.7$.

and Q_{req} at least once. Again, we target at one-time deployment in this experiment.

7.1. Transient behaviors

We run our sensor deployment algorithm to obtain the minimum number of wireless sensors required and their placements. From the traces, we found that at least 9 sensors are required in our algorithm to satisfy the expected $P_{req} = 0.5$ and $Q_{req} = 0.5$ over the sensing field. Fig. 11 shows the coverage satisfaction probability of the grid cells over time after deploying the sensors. The results show that our sensor deployment can always guarantee a satisfaction coverage probability greater than 0.5, while uniform and random deployments with same number of sensors can satisfy this requirement only in certain hours. The coverage probability of the field without sensors is also plotted for comparison. Similarly, the average sensing quality of the grids is shown in Fig. 12. It demonstrates that our deployment can always provide the best average sensing quality among the three different deployments.

We then repeat the experiment by increasing both the expected P_{req} and Q_{req} to 0.7. We found that at least 13 sensors are required to satisfy the expected $P_{req} = 0.7$ and $Q_{req} = 0.7$ over the sensing field. Fig. 13 shows the coverage satisfaction probability of the grid cells over time after deploying the sensors. Again, the results show that our sensor deployment can always guarantee a satisfaction coverage probability greater than 0.7, while not always the case for uniform and random deployments. The coverage probability of the field without sensors is also plotted for comparison. Fig. 14 demonstrates that our deployment can always provide the best average sensing quality among the three different deployments. The results of our algorithm here can achieve higher satisfaction probability and coverage compared with Figs. 13 and 14.

We set the expected $P_{req} = 0.9$ and $Q_{req} = 0.9$ for a higher level of requirements. It turns out that 18 sensors are required for our algorithm to achieve these requirements. Fig. 15 shows that our sensor deployment can always guarantee a satisfaction coverage probability greater than 0.9. Although 18 deployed sensors can greatly increase the satisfaction coverage of uniform and random deployments, they are not able to satisfy the expected $P_{req} = 0.9$ and $Q_{req} = 0.9$ requirement in certain all hours. Similarly, the average sensing quality of the grids is shown in Fig. 16. Again, it demonstrates that our deployment can achieve the best average sensing quality among the three different deployments. In summary, the above experiments show that our algorithm out perform both uniform deployment and random deployments, which are unable to provide the required sensing performance even with the same number of stationary sensors.

7.2. Varying percentage of training data

We show the performance of our sensing system by utilizing only a subset of the mobility traces as training data in this experiment. All of the available mobility traces remains as testing data to evaluate the satisfaction coverage probability and average sensing quality after sensor deployment. Only 10%, 25% and 50% of the available mobility traces are randomly selected as the training data.

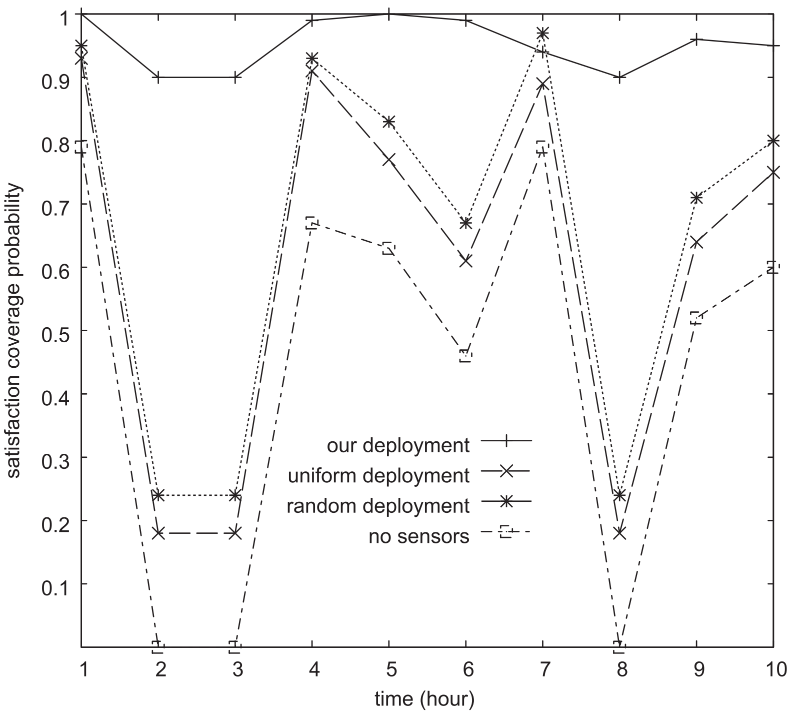

Fig. 15. Coverage satisfaction probability with one-time deployment at $P_{req} = 0.9$ and $Q_{req} = 0.9$.

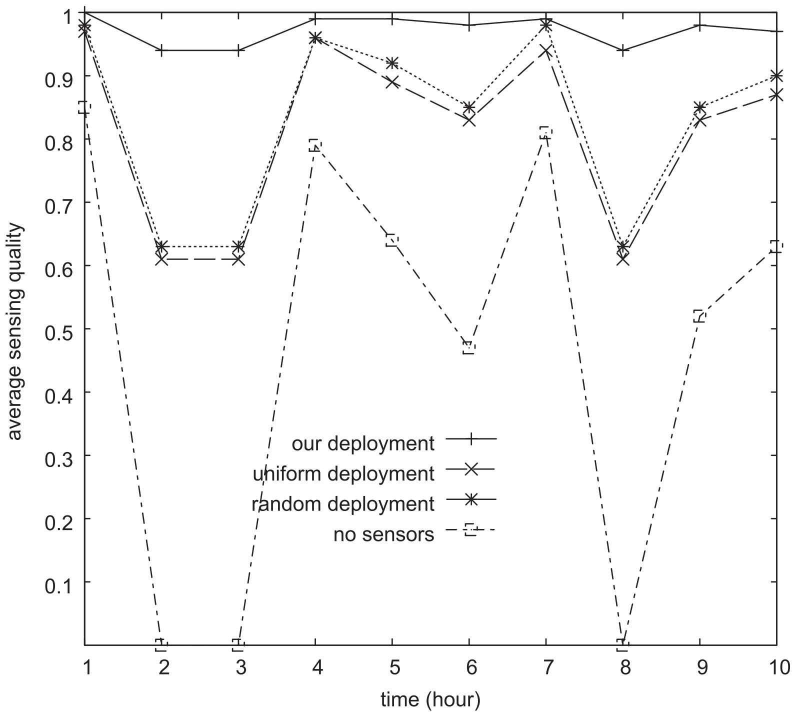

Fig. 16. Average sensing quality with one-time deployment at $P_{req} = 0.9$ and $Q_{req} = 0.9$.

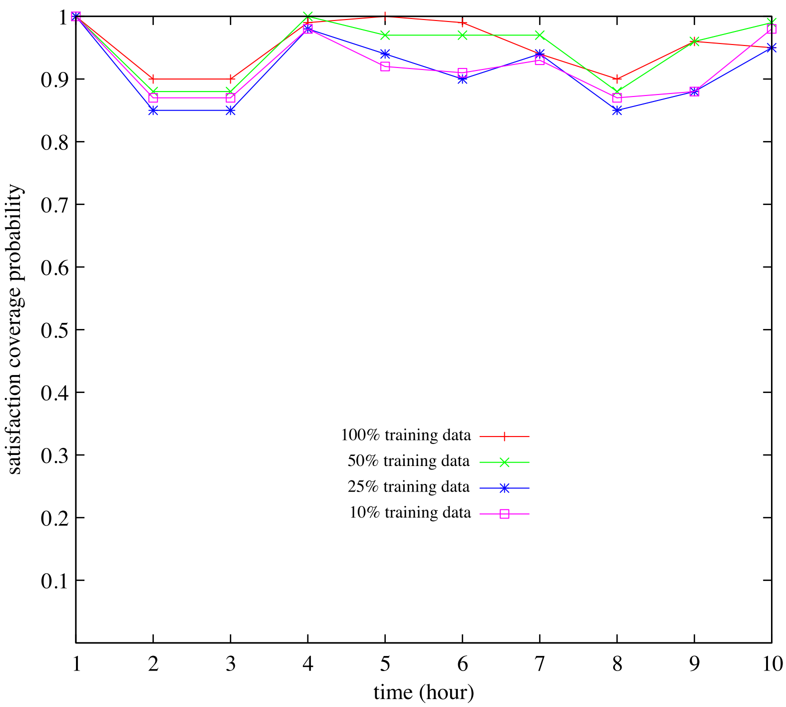

Fig. 17. Coverage satisfaction probability at $P_{req} = 0.9$ and $Q_{req} = 0.9$ with different percentage of training data.

Figs. 17 and 18 show that our system can achieve comparable satisfaction coverage probability and average sensing quality even with reduced percentage of training data. It implies that a small number of training data is representative to a greater testing dataset for sensor deployment in our system.

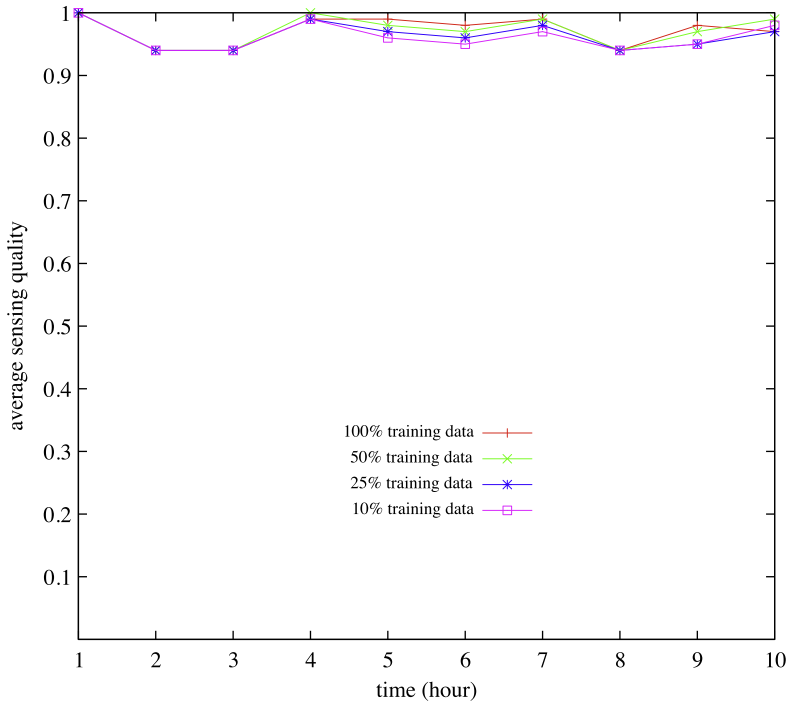

Fig. 18. Average sensing quality at $P_{req} = 0.9$ and $Q_{req} = 0.9$ with different percentage of training data.

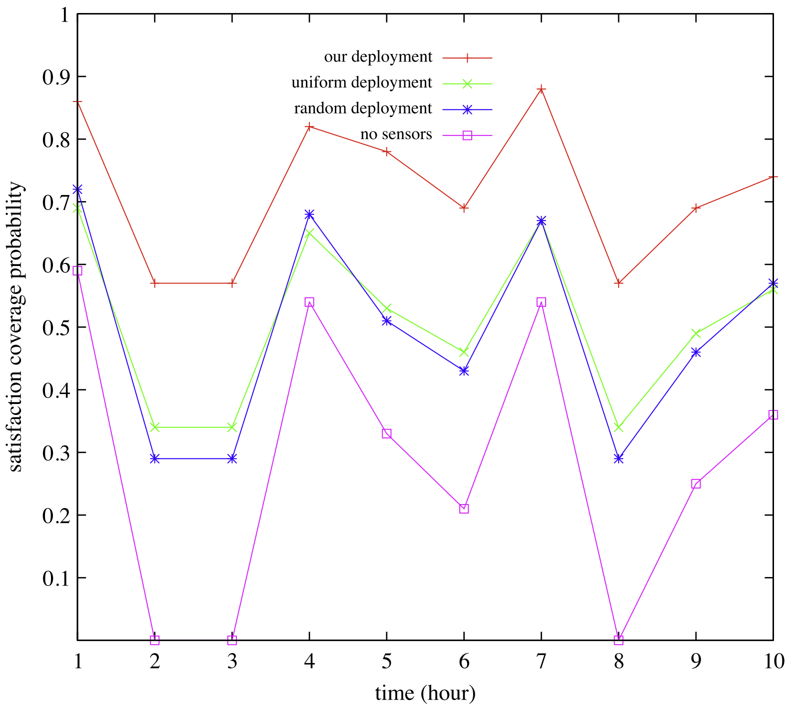

Fig. 19. Coverage satisfaction probability at $P_{req} = 0.5$ and $Q_{req} = 0.5$ with reduced grid size.

7.3. Reduced grid size and sensing capability

We repeat our experiments with more fine-grained grid cells of size 50 m × 50 m. We set $P_{req} = 0.5$ and $Q_{req} = 0.5$. The sensing coverage of both mobile phones and sensors are reduced to half of the original. We found that at least 15 sensors are needed to achieve the required sensing quality and coverage with our deployment algorithm. Figs.

19 and 20 show the coverage satisfaction probability and average sensing quality of different sensor deployment algorithms with 15 sensors. The results indicate that our algorithm works better than both uniform and random sensor deployments. Compared with Figs. 11 and 12, this experiment achieves lower satisfaction coverage probability and average sensing quality even with more deployed sensors due to the reduced sensing capability of nodes.

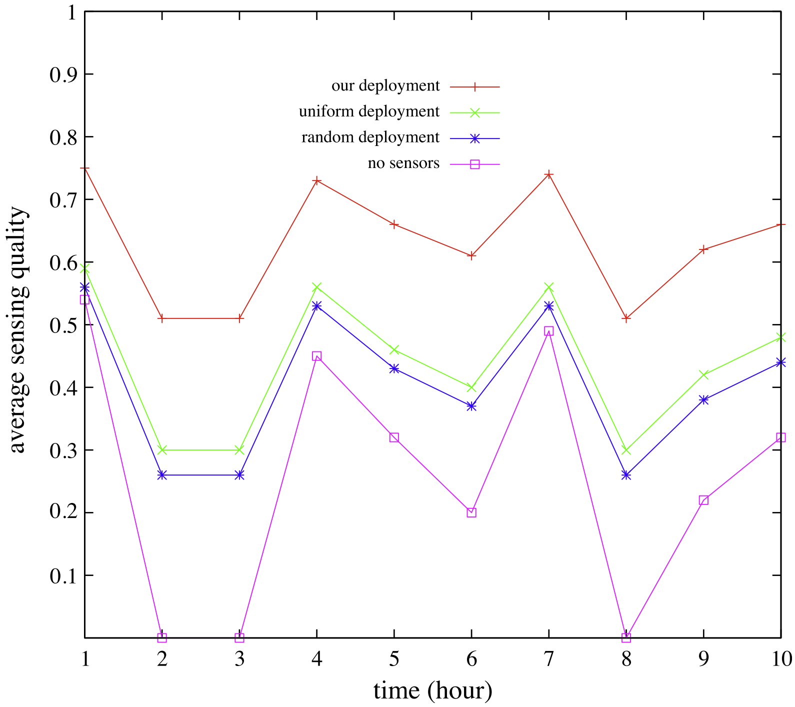

Fig. 20. Average sensing quality at $P_{req} = 0.5$ and $Q_{req} = 0.5$ with reduced grid size.

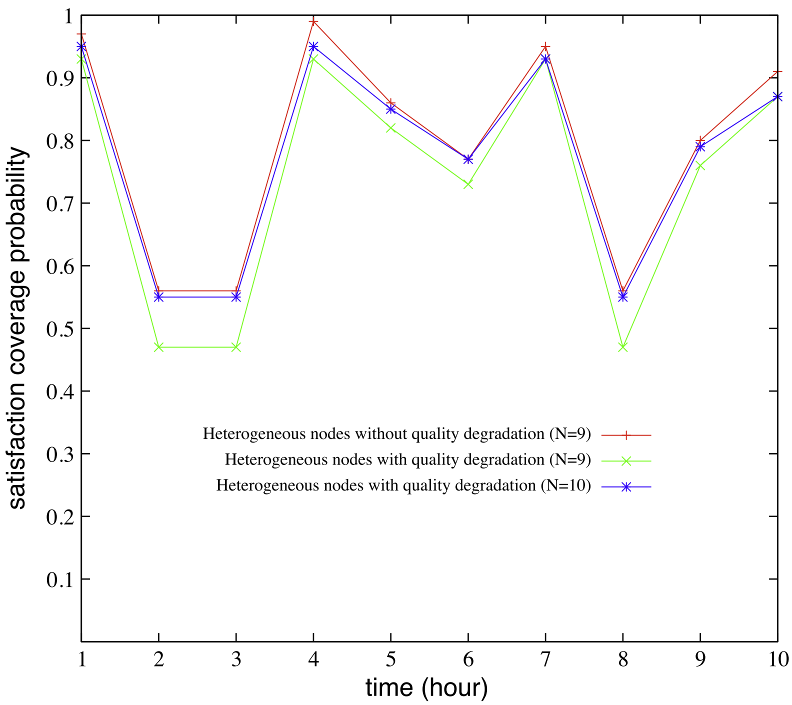

Fig. 21. Coverage satisfaction probability at $P_{req} = 0.5$ and $Q_{req} = 0.5$ with heterogeneous nodes in changing environment.

7.4. Heterogeneous sensors in changing environment

We repeat our experiments to evaluate the sensing performance of heterogeneous nodes in a changing environment. Fifty percentage of the mobile phones have reduced sensing quality to only half of the original due to their weaker sensing capability. Moreover, both the mobile phones and stationary sensors may have sensing quality

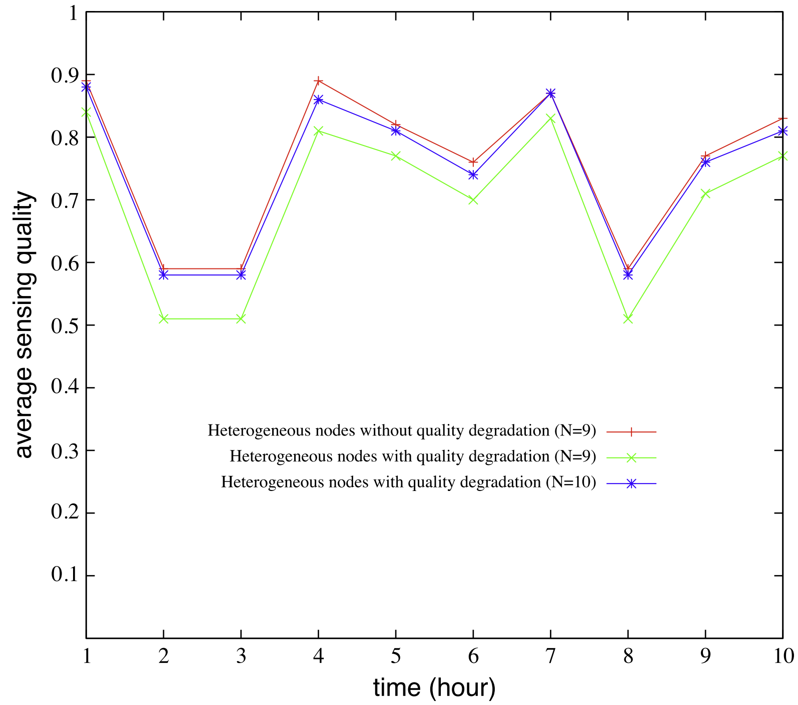

Fig. 22. Average sensing quality at $P_{req} = 0.5$ and $Q_{req} = 0.5$ with heterogeneous nodes in changing environment.

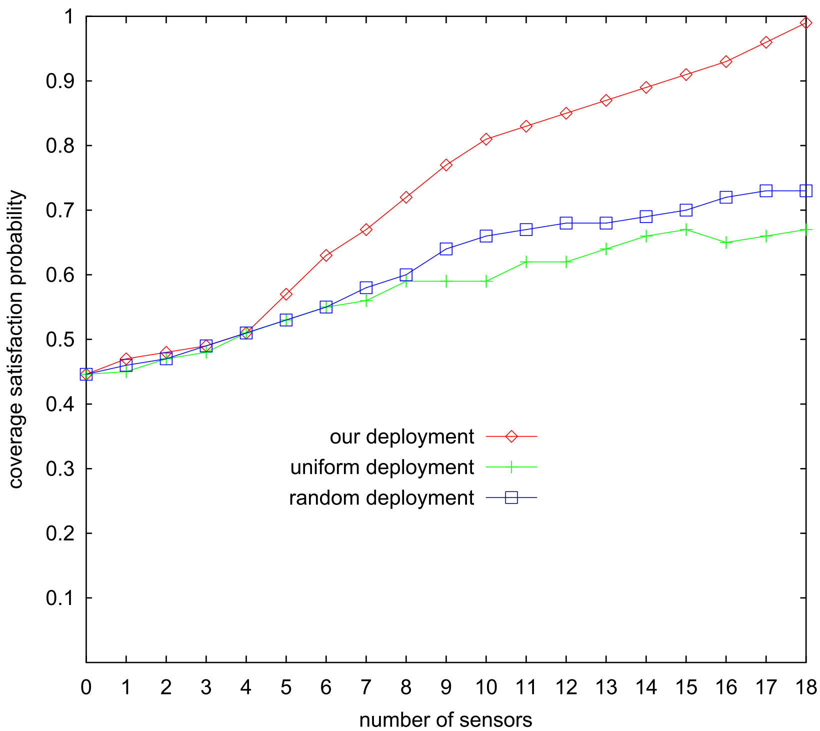

Fig. 23. Coverage satisfaction probability varying number of sensors.

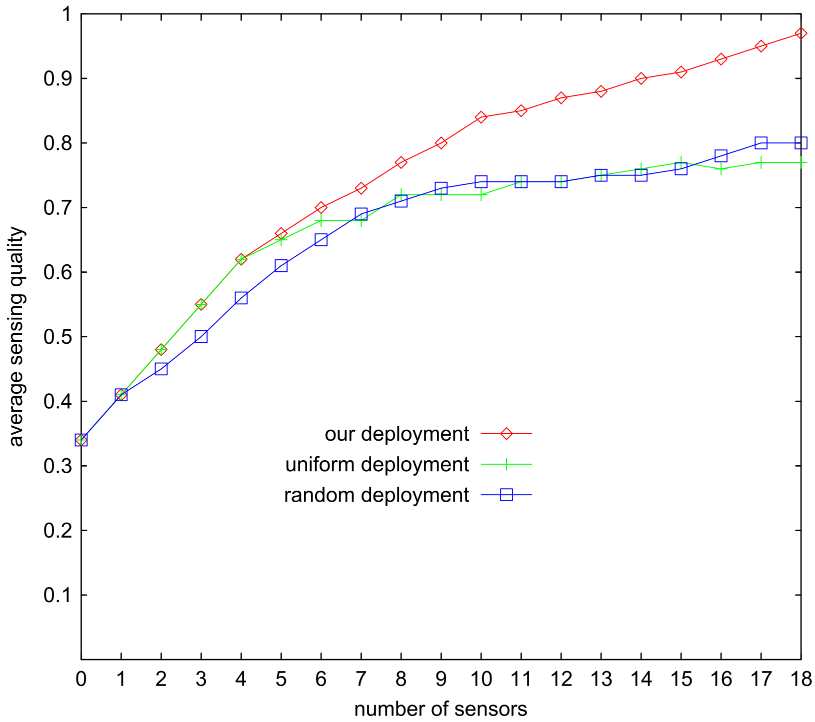

Fig. 24. Average sensing quality varying number of sensors.

degradation at different moments due to the changing environment. Twenty percentage of them may have a quality degradation of 20%. Another 30% of them may have a quality degradation of 30% during the experiment. Figs. 21 and 22 show the coverage satisfaction percentage and average sensing quality at $P_{req} = 0.5$ and $Q_{req} = 0.5$. From the results, 9 sensors are no longer enough to achieve the required P_{req} when there is quality degradation due to the heterogeneous nodes in changing environment. After taken the potential degradation into account for the deployment, we find that 10 sensors are needed to achieve the required sensing coverage and quality.

7.5. Varying number of deployed sensors

Next, we examine the satisfaction coverage probability and the average sensing quality varying the number of sensors (see Figs. 23 and 24). Our deployment can always achieve higher satisfaction probability and average sensing quality than both uniform and random sensor deployments. The results confirm that our sensor deployment algorithm can reduce the number of sensors effectively, while guaranteeing satisfactory sensing coverage and sensing quality.

8. Conclusions and future works

We propose a framework for wireless sensor network deployment in mobile phone assisted environment. We suggest that wireless sensors and mobile phone participants can perform sensing collaboratively and complement each other. Our framework predicts the sensing quality of the mobile phone participants considering their mobility and sensing behaviors. Then, it provides wireless sensor deployment minimizing the number of sensors, while guaranteeing satisfactory sensing quality and coverage. Our framework includes several sub-models which offers high level of flexibility. It can adapt to different kinds of sensing campaigns by replacing any of the sub-models accordingly. Extensive evaluations with real mobile traces have shown that our framework can provide good coverage and sensing quality in most of the grid points with small number of additional wireless sensors. We believe that the performance of our framework will improve further if we understand the behavior and motion patterns of the participants thoroughly in real campaigns.

Acknowledgments

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