Wireless Sensor Network Deployment in Mobile Phones Assisted Environment

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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.

I. Introduction

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 static sensors being deployed carefully at chosen locations. Although individual sensor node is not very expensive, large deployment of sensor nodes in the network could make the total cost considerably high. In the meantime, mobile phones are becoming very popular and more powerful which make participatory sensing possible [1], [2]. Some mobile phones could also be used as sensors to collect data such as sound, motion, temperature, etc.

Mobile phone users could collect data at different time and locations when they move around. The phones are regularly charged and no extra deployment cost is involved in participatory sensing. 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 static 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 static sensors and mobile phones. In particular, we aim at providing collaborative sensing by both mobile phone participants and static 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 static 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 II presents related work. In Section III, we describe the system architecture for collaborative sensing with wireless sensors and mobile phone. In Section IV, 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 V, together with detailed descriptions of the three modules. In Section VI and VII, 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 VIII.

II. Related Work

Participatory sensing has been studied recently to provide mobile phone-based data gathering [1]. 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. In our work, we mainly focus on two aspects, which are evaluation of participants' sensing quality and availability. Reddy et al. proposed a model for evaluating participation and performance in participatory sensing based on Beta distribution [3]. 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 [2]. 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 static sensors for collaborative sensing with mobile phone participants.

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 [4]. Their scheme turns off some redundant nodes and guarantees that the original sensing coverage is maintained. Dhillon et al. proposed two greedy algorithms for deployment of wireless sensor network [5]. 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 [6]. They formulated the problem with integer linear programming. Poduri et al. proposed an algorithm based on artificial potential fields for the self-deployment of a mobile sensor network [7]. 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 static sensors and mobile phone participants complement each other to provide satisfactory sensing services with minimized cost.

III. 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.

A. 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 [8]. Although we can find sensors that support WiFi [9] and bluetooth [10], they are not very common. On the other hand, most of the mobile phones are equipped with GPRS, WiFi, bluetooth and infra-red nowadays [11], but they are rarely Zigbee enabled [12]. 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 [13] which supports IEEE 802.11b/g and is equipped with UBS ports for connecting to the sensors. Alternatively, we can connect a mobile phone such as Nokia N810 [14] through its USB port or a IEEE 802.15.4/ZigBee USB adapter [15] 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 Figure 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

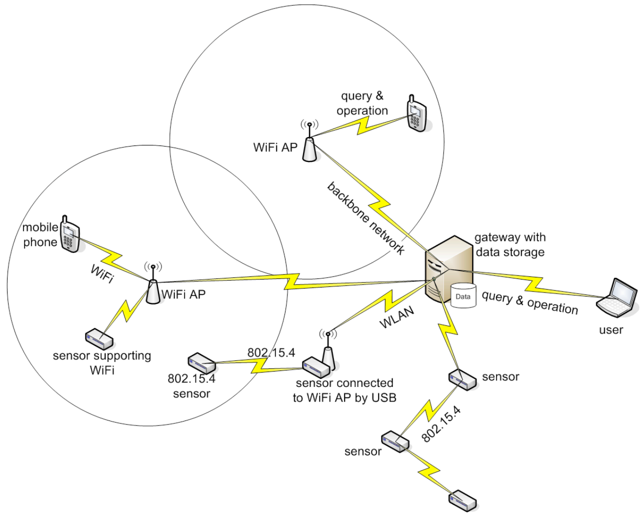

Fig. 1. System architecture

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

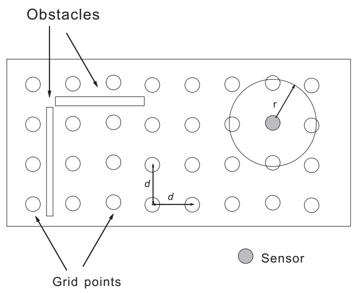

Fig. 3. Sensing field with obstacles

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.

B. Collaborative Sensing with Sensors and Mobile Phones

The network can be deployed in different places to monitor the environment and human activities. Some potential sensing environments include amusement parks, universities, tourist attractions, etc. Figure 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 consider some primary sensing data like the noise level and pictures 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.

IV. The Sensor Placement Problem in Sensor-Mobile Phone Collaboration Paradigm

A. 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 et al. for the detection probability of a target by a sensor in a terrain of sensing area [5]. 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

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

where γ can be used to model the quality of the sensor and the rate at which its detection probability diminishes with distance. 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. Figure 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 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

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

Note that 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.

B. 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 $< Q_i, P_i >$, 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 $\mathbf{Q_{req}} = (Q_1 Q_2 ... Q_N)$ and $\mathbf{P_{req}} = (P_1 P_2 ... P_N)$ 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.

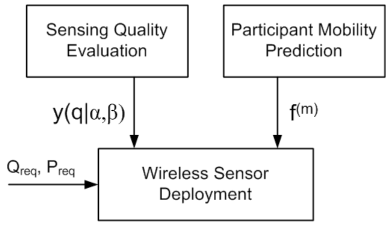

Fig. 4. Overview of our framework

V. 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 Figure 4). The implementation of every module can 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.

A. Evaluation of Sensing Quality of Participants

The sensing quality of participants are affected by many human factors, like community expertise [16], 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 [3].

Evaluating sensing quality of participants has an inherent relation with reputation evaluation of transaction parties in e-commerce [17]. 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 [18]. 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 travelling, 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 [3], [19]. 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, $0 \leq q \leq 1$, 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 i^{th} outcome, we define random variables r_i and s_i as follows

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

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

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

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

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

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

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 $< r_i, s_i >$, 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

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

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

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

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 $\int_Q^1 y(q|(\alpha, \beta))\mathrm{d}q$.

B. 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

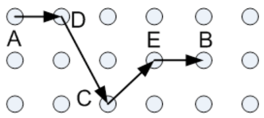

Fig. 5. Example of participant motions

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. Figure 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 modelled by a Markov chain $\{c_1, c_2, ..., c_n\}$. Each state c_i corresponds to the grid point g_i in the sensing field.

According to the property of Markov transition matrix X, $p_{i,j}^{(n)}$ 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 $\mathbf{f^{(0)}} = (f_1^{(0)} f_2^{(0)} ... f_n^{(0)})$ of the participants in a period T, which can be obtained by some statistics from the previous participants' actions.

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

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

$$\mathbf{f^{(m)}} = (f_1^{(m)} f_2^{(m)} ... f_n^{(m)})$$

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

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

Repeated application of this recursive equation yields

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

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

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

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

C. Cost-Effective Deployment of Wireless Sensors

Given the corresponding sensing requirement $< Q_i, P_i >$ 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 $i = 1...N$ 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**
    $p_x = \int_{Q_i}^{1} y_x(q|\alpha, \beta) \mathrm{d}q$;
    for all g_j is a grid point **do**
      if $d_{j,i} p_x > Q_{req}$ **then**
        $Pr_i = Pr_i \prod_{t=0}^{T} (1 - f_j^{(t)})$;
      end if
    end for
  end for
  $Cov_i^T = 1 - Pr_i$;
end for

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

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

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 $\mathbf{M} = (M_1 M_2 ... M_n)$ and M_i is the missing probability that a grid point g_i needs to be covered by extra wireless sensors. Intuitively, the higher the missing probability for a grid, the greater need for a sensor to be deployed there. The coverage problem in sensor networks has been proven as a NP-hard problem and heuristic algorithms have been suggested for solving related problems [5], [20].

We propose a greedy algorithm for sensor deployment considering the sensing quality and probability of mobile phone participants (see Algorithm 2). Our algorithm attempts to increase the coverage of the grid points that are covered least effectively. We adopt a heuristic approach to determine the best placement of the next sensor at a time.

We initialize q_i as the required sensing quality Q_i for all grids g_i with missing probability $M_i > 0$. We define u_i to be the gain if a new sensor is placed at grid g_i. u_i indicates the missing probability that a sensor can reduce in proportion to the required sensing quality Q_i. A new sensor will be placed at the grid that reduce the missing probability the most, i.e. maximum gain u_i. The grids which are covered by the newly added sensors will have their missing probability reduced. Only grids with missing probability $M_i > 0$ will be considered in our algorithm. When a grid achieves a sensing quality greater than Q_i, i.e. $q_i = 0$, it will be removed from the missing list by setting $M_i = 0$. The algorithm is iterative and terminated when all grid points are covered with the required probability, or the upper limit of the number of sensors is reached.

Algorithm 2 Deployment of wireless sensors

Sensors_num = Sensors_max;
for each g_i with $M_i > 0$ **do**
  $q_i = Q_i$;
end for
while ($\exists M_i > 0$) and (Sensors_num> 0) **do**
  for each g_i **do**
    $u_i = \sum_{\forall j} M_j \frac{d_{i,j}}{Q_j}$;
  end for
  Find g_{i^*} with the maximum u_{i^*};
  for each g_j **do**
    $q_j = q_j - d_{i^*,j}$;
    if $q_j \leq 0$ **then**
      $M_j = 0$;
    end if
  end for
  Sensors_num = Sensors_num-1;
end while

VI. 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

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

A. Deployment Allows Reconfigurations

In the first experiment, we consider a campaign with 3 mobile phone participants. The whole campaign lasts for 200 days which are divided into 10 periods. Re-deployment is allowed at the beginning of each period. 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.

Figure 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.

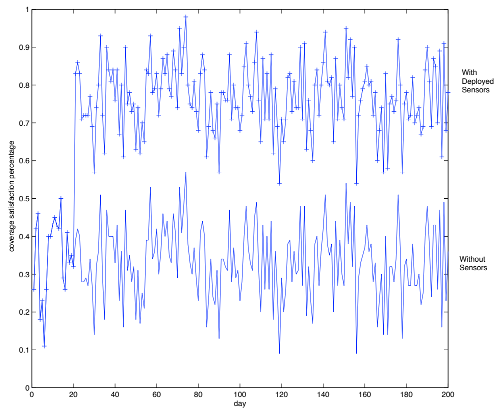

Fig. 6. Comparison on coverage satisfaction percentage with required coverage of 0.9

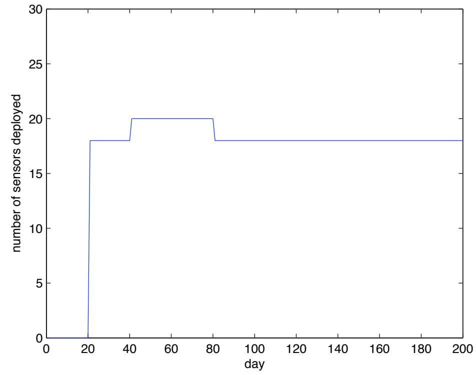

Fig. 7. Number of sensors deployed with required coverage of 0.9

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. Figure 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.

B. 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 Figure 8. The figure shows that our proposed sensor deployment algorithm can achieve much better coverage satisfaction percentage than the random

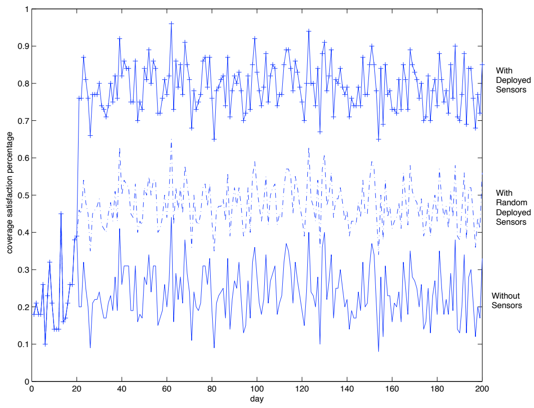

Fig. 8. Comparison on coverage satisfaction percentage with one-time deployment

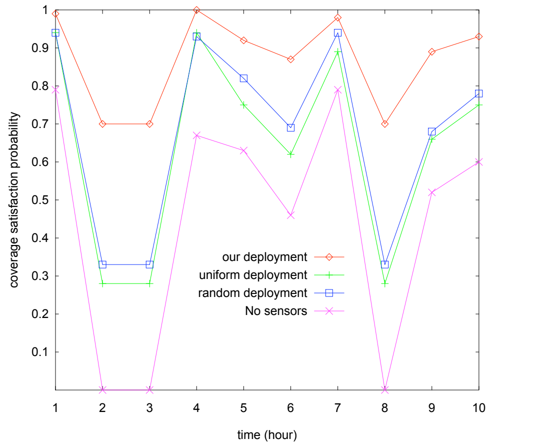

Fig. 9. Coverage satisfaction probability with one-time deployment

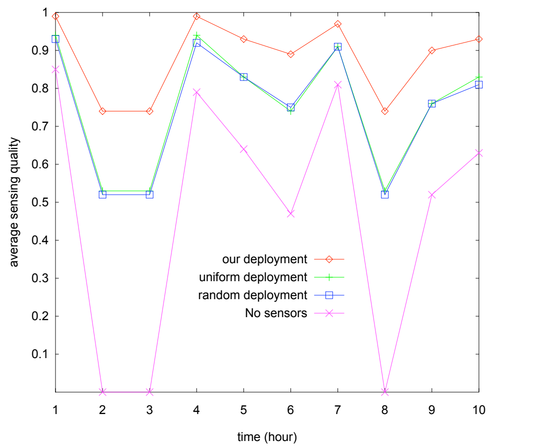

Fig. 10. Average sensing quality with one-time deployment

deployment algorithm. The coverage satisfaction probability of random 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.

VII. 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) [21], [22]. The human mobility traces are collected with GPS receivers carried by 41 participants at every 10 seconds. These traces are mapped into a two dimensional area and recomputed to a position at every 30 seconds by averaging three samples over that 30 second period to account for GPS errors [21].

We monitor a 1km x 1km area at the center of the theme park with our framework considering the mobile traces of 10 hours. The sensing area is divided into 10x10 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 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 $P_{req} = 0.7$ and the expected sensing quality $Q_{req} = 0.7$ 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} and Q_{req} at least once.

Again, we target at one-time deployment in this experiment. 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 13 sensors are required to satisfy the expected P_{req} and Q_{req} over the sensing field. Figure 9 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 0.7, 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 Figure 10. It demonstrates that our deployment can always provide the best average sensing quality among the three different deployments.

Next, we examine the satisfaction coverage probability and the average sensing quality varying the number of sensors (see Figures 11 and 12). 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

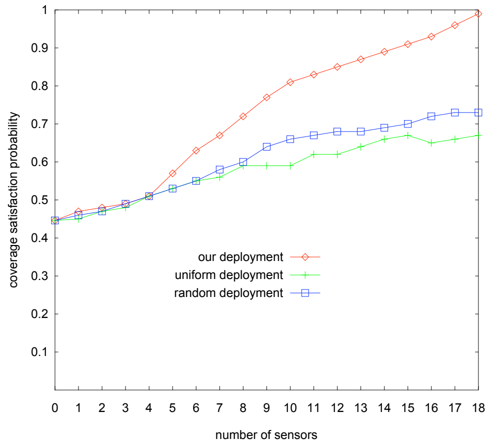

Fig. 11. Coverage satisfaction probability varying number of sensors

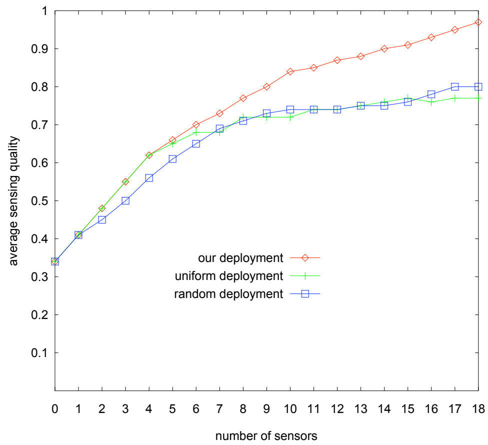

Fig. 12. Average sensing quality varying number of sensors

coverage and sensing quality.

VIII. 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.

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