Probabilistic Field Coverage using a Hybrid Network of Static and Mobile Sensors

Dan Wang*, Jiangchuan Liu*, Qian Zhang†

* School of Computing Science, Simon Fraser University, Burnaby, British Columbia, Canada, V5A 1S6, Email: {danw, jcliu}@cs.sfu.ca

† Department of Computer Science, Hong Kong University of Science and Technology Clear Water Bay, Kowloon, Hong Kong, Email: qianzh@cs.ust.hk

***Abstract*— Providing field coverage is a key issue in many sensor network applications. For a field with unevenly distributed static sensors, a quality coverage with acceptable network lifetime is often difficult to achieve. We propose a hybrid network that consists of both static and mobile sensors, and we suggest that it can be a cost-effective solution for field coverage. The main challenges of designing such a hybrid network are, first, determining necessary coverage contributions from each type of sensors; and second, scheduling the sensors to achieve the desired coverage contributions, which includes activation scheduling for static sensors and movement scheduling for mobile sensors.**

In this paper, we offer an analytical study on the above problems, and the results also lead to a practical system design. Specifically, we present an optimal algorithm for calculating the contributions from different types of sensors, which fully exploits the potentials of the mobile sensors and maximizes the network lifetime. We then present a random walk model for the mobile sensors. The model is distributed with very low control overhead. Its parameters can be fine-tuned to match the moving capability of different mobile sensors and the demands from a broad spectrum of applications. A node collaboration scheme is then introduced to further enhance the system performance.

We demonstrate through analysis and simulation that, in our hybrid design, a small set of mobile sensors can effectively address the uneven distribution of the static sensors and significantly improve the coverage quality.

I. Introduction

Wireless sensor networks have recently been suggested for many protection and surveillance applications. One key objective of these applications is to detect abnormal events in a sensing field, which depends on the coverage quality of the sensor network. The *k-coverage* is a common criterion, where any point in the sensor field should be covered by k sensors [18]. For many applications, it turns out that a deterministic k-coverage is too expensive and not necessary. Therefore, probabilistic coverage [7][22] is introduced and every point is covered with certain probability ratio. This ratio tunes the coverage quality and allows the sensors to switch between sleeping and working states.

In these studies, only static sensors are used. The quality of coverage is noticeably affected by the initial deployment of the sensors. For uneven sensor distributions, the sensors in a sparse area may have to stay active longer to ensure the coverage quality. The batteries of these sensors will be depleted earlier and thus making the area even sparser. In an extreme case, an area will be uncovered by any sensor, leaving a hole in the field. Unfortunately, such unfavorable sensor distributions are inevitable in many applications where a well-controlled or manual deployment is not practical.

Recent advances of embedded hardware and robot have made mobile sensors possible. The mobile sensors have the same sensing capability as static sensors, but are able to move in a field, and their batteries are generally rechargeable. In other words, their lifetime is not bounded by the limited battery. While fully mobile sensor networks remain expensive and are complicated by information exchange, we envision that a hybrid network with both static and mobile nodes can be a cost-effective tool for coverage with unevenly distributed sensors. A related design was presented in [19], which suggested a one-time reposition of the mobile sensors after the initial deployment. This solution, however, proves inadequate for balancing the sensor coverage and load in many applications. Consider Fig. 1, where there are a number of static sensors and three mobile sensors to cover a field. Each sensor can cover its associated grid. If there are no mobile sensors, grid 6 will never be covered. If only one-time repositioning for the mobile sensors is employed, the coverage can be enhanced, but there will still remain grids with permanently fewer sensors.

In this paper we propose a hybrid sensor network which fully exploits the movement capability of the mobile sensors. In our solution, the mobile sensors are always in motion to assist the static sensors; the occurrence probability of the mobile sensors in each grid, or their contribution for covering the grid, is adaptively determined according to the network configuration. From a statistical point of view, the overall coverage is enhanced, and energy consumption of the static sensors is more balanced.

The main challenges in designing such a hybrid network are, first, to clarify the necessary coverage contributions from the static and mobile sensors; and second, to find a mobility model for the mobile sensors to achieve their desired coverage contribution. In this paper, we for the first time offer an analytical study on the above problems, and the results also lead to a practical system design. Specifically, we present an optimal algorithm for calculating the contributions, which fully explores the potentials of the mobile sensors and maximizes

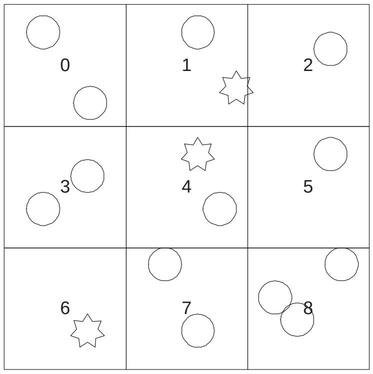


Fig. 1. Field covered by a hybrid static and mobile sensor network, circles representing static sensors and stars representing mobile sensors.

the network lifetime. We show that the contribution from the static sensors can be achieved through a simple random sleep/work scheduling. We then present a random walk model for the mobile sensors that achieves the coverage contribution.

Our hybrid architecture is general enough and offers a promising baseline for the demands from diverse applications. Various enhancements can be integrated to improve system performance. Indeed, we point out several interesting observations from this hybrid design. Particularly, a *wall effect* may prevent mobile sensors from moving freely in a field. We effectively solve this problem through an optimal mobile sensor allocation algorithm. We then outline a sensor collaboration scheme which further enhances the system performance.

The rest of the paper is organized as follows. In section II, we present the related work. We outline our hybrid network architecture in section III. The respective contributions from static and mobile sensors are derived in section IV. Section V discusses the random walk based mobility model and solutions for the wall effect. In section VI, we present an in-network collaboration protocol to avoid redundant activation. The performance of the hybrid sensor network is evaluated in section VII. Finally, section VIII concludes the paper.

II. Related Work

Wireless sensor networks have been widely studied in recent years, focusing on those with static sensors; a survey can be found in [1]. The effective coverage using static sensors is one of the key problems in sensor network applications, and has been examined in various aspects, such as field/path coverage and determinstic/probabilistic coverage. Related work can be found in [7][18][23] and the references therein. Many studies propose grouping the sensors into grids [7][21][22], where all sensors in a grid are equivalent in their functionality, such as coverage capability. The surveillance systems in [7][23] further suggest that the static sensors can be redundantly deployed and work in turn to extend the lifetime of the system. Our configurations for the static sensors are motivated by their work, but emphasize on the interactions with mobile sensors.

The advances in embedded systems and hardware designs have realized mobile sensors, such as Robomote [17] and Khapera [14]. Unlike the static sensors, which are tightly constrained by the energy supplies, their batteries are rechargeable. Recent work also suggests that much longer working time and shorter recharging time can soon be expected [10].

The mobility model of mobile nodes has long been a classic problem in ad hoc and cellular wireless network research. The random walk, random waypoint walk, random trip, and fluid models have been widely used to capture the mobile behaviors. A survey and comparison of these models can be found in [16]. However, most of them analyze the mobility behaviors, while not for guiding the movement of the mobile nodes.

Using mobile sensors for coverage is recently considered in [13][19]. Liu et al. [13] extend the definition of coverage, which is originally given in static geographic sense, into the time domain. Informally, the coverage is evaluated as the fraction of the covered area at a point of time. They conclude that, compared to using uniformly distributed static sensors, it is more beneficial if all sensors are mobile and are traveling in a random walk fashion. A more recent study on the velocity and motion strategies for all mobile sensor networks to improve coverage can be found in [3]. While this theoretical result is elegant and exciting, the mobile sensors remain expensive nowadays; it is unlikely a fully mobile sensor network is practical in the near future. In addition, when all the sensors are in random motion, packet routing and information dissemination will be much more complicated.

We thus envision a hybrid sensor network consisting of both static and mobile sensors. If the number of the mobile sensors is small, the cost of building such a network remains acceptable, and the performance could be significantly improved, as shown in our study. A closely related idea is presented in [19], which compensates poor initial sensor distributions by strategically repositioning some mobile sensors. The key difference here is that we consider continuous movement for the mobile sensors, while they focus on one-time repositioning. Some other one-time reposition schemes can be found in [8][9][25] and a common drawback is that, after the mobile sensors are reposited, the field coverage may still be unbalanced, possibly leaving coverage holes. Our proposal can be viewed as a generalization of the one-time repositioning, and we demonstrated the potential benefit of continuous movement through analytical and experimental results.

III. Architecture Overview

A. Hybrid Network Model

The hybrid network in our study consists of both static and mobile sensor nodes, which collectively monitor a field of interest. As in previous studies [6][12][22], we assume that the field is divided into n^2 virtual grids, indexed from 0 to $n^2 - 1$[1]. This virtual grid structure is not special, and we have shown in [20] that our analysis and algorithms can be easily extended to hexagon or other virtual structures. Through GPS or available positioning services [2][4], the sensors are aware of their location information and, hence, their associated grids. The size of each grid is $\frac{\sqrt{2}}{2}R \times \frac{\sqrt{2}}{2}R$, where R is the sensing range of a static sensor. Thus, any active sensor in a grid can

[1] In this paper, we use the grids to denote a grid of n^2 cells.

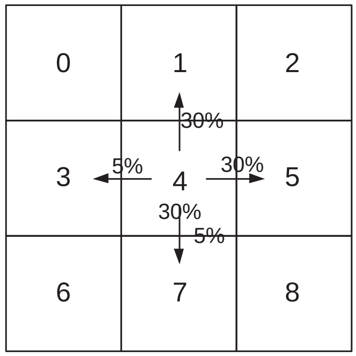


Fig. 2. The movement of a mobile sensor. The probabilities for moving to or staying in a grid are determined according to the network configuration.

cover the whole grid. The sensing range of a mobile sensor can be smaller, e.g., $\frac{R}{2}$, as it can reposit itself to the center of its grid. An example of the grid structure is shown in Fig. 1.

When a sensor detects an abnormal event in its grid, it should report the event to a predefined agent. The reporting mechanism is out of the scope of our study, and existing virtual grid based algorithms can be used [22].

Given that the static sensors in one grid are equivalent in coverage, they do not have to be active simultaneously, so as to save energy. The deployment of the static sensors is often nonuniform; and even worse, holes (grids with no static sensors) can exist, creating permanently uncovered regions[2]. In our hybrid network the mobile sensors are always active, and can stay in a grid or move to other grids, as shown in Fig. 2. This feature can help with the covering of the holes in the field and reducing the load of the existing static sensors.

B. Performance Measurement

Since our main goal is covering related, we define a measure of how well a location is covered. Similar measurement is also used in [21].

Definition 1: A sensor field is said to be δ-covered if, at any point in time, at least an expected $\delta \in (0, 1)$ fraction of the whole area is covered by one or more active sensors[3].

Assume that δ is the minimum coverage ratio required by the user, our objective is to ensure this quality, while maximizing the lifetime of the network.

It is worth noting that the battery of state-of-the-art mobile sensors is rechargeable [10]; hence, the lifetime of the whole network is bounded by that of the static sensors. We use the lifetime of the first dying out sensor as a measure for the system lifetime. This definition has been widely used in existing studies [5][24], and essentially suggests a load-balanced operation for the static sensors. The effectiveness of this definition has been validated by our simulation results in Section VII. From a functional point of view, once the first static sensor dies, its grid needs additional assistance from the mobile/static sensors, which in turn increases the workload of other static sensors, resulting in a domino effect that quickly drains the power of the whole network. Thus, the death of the first sensor serves as a good signal to the end of the steady-state operation.

In summary, given a coverage requirement, the network lifetime depends on the activation models of the static sensors, which further depend on the sensor distribution and the potential contributions from the mobile sensors.

C. Working and Moving Models

Given the system model and the performance measures, a natural question is what kind of working and moving models of the sensors can achieve the coverage objective. In our basic framework, we adopt a random activation scheduling for the static sensors, and a random walk model for the mobile sensors. More specifically, our hybrid sensor network goes through the following stages:

1) *Parameter Initialization:* After deployment, one or more mobile sensors travel around the field and collect the distribution information of the static senors in all grids. The mobile sensors determine the movements of themselves as well as the activation probability of the static sensors. The mobile sensors then notify the static sensors of their activation probability.

2) *Field Monitoring:* Consider the time slots are discrete. In each time slot, a static sensor independently activates itself with the activation probability obtained in the initialization stage and then monitors its grid. Each mobile sensor independently decides to move into one neighboring grid or to stay in the current grid, and then monitors the grid where it resides.

The advantages of using a probabilistic operation over a deterministic one are many. First, our technique is easier to implement because it involves simple optimization in the initial stage for the sensors. Second, the behavior of each type of the sensors are statistically identical. This is useful especially for recharging or replacement of mobile sensors. The substitute mobile sensor can easily follow the mobility model and continue to monitor the sensor field, regardless of the current state of other sensors; whereas a deterministic scheme may involve re-optimization. Third, a probabilistic coverage is generally more resistent to intruders that try to learn the sensor behavior.

Our hybrid architecture offers achievable and reasonably good solutions to the problem of the uneven distribution of static sensors. It is, however, worth emphasizing that the above framework provides only a flexible baseline for further design of hybrid systems. Many practical enhancements could be added, and we will discuss some of them as well.

IV. Coverage Contributions from Static and Mobile Sensors

In our hybrid network, the coverage of a grid is achieved by the combined efforts of static and mobile sensors. A grid is said to be covered at time t if either a static sensor in this grid is active or a mobile sensor resides in the grid at time t. To balance the workload, it is desirable to assign the static sensors with an identical activation probability p. An

[2]Even if the deployment is a globally uniform distribution, local fluctuations still would occur, resulting in uneven numbers of sensors in different grids.

[3]Notice that in this definition, we are more restricted as we request in every point of time, the expected coverage is above δ.

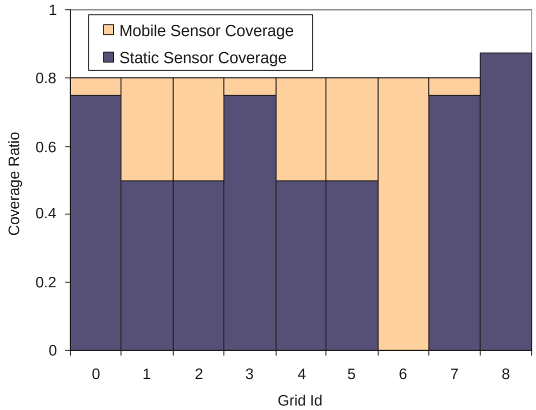


Fig. 3. Coverage contributions from static and mobile sensors. Coverage ratio $\delta = 0.8$, and activation probability of static sensors $p = 0.5$.

Algorithm CalcContribution()

1 SortGrid();

2 **for** ($\mathcal{K} = 0$; $\mathcal{K} < n^2$; $\mathcal{K}$++)

  $/ *\ (1-p)^{d(l_{\mathcal{K}})} \leq 1 - \delta\ * /$

3   $p = 1 - \sqrt[d(l_{\mathcal{K}})]{1-\delta}$;

4   **for** ($i = 0$; $i < \mathcal{K}$; i++)

    $/ *\ (1-p)^{d(l_i)} \times (1 - \pi_{l_i})^M \leq 1 - \delta\ * /$

5     $\pi_{l_i} = 1 - \sqrt[M]{\frac{1-\delta}{(1-p)^{d(l_i)}}}$;

6   **if** ($\sum_{i=0}^{n^2-1} \pi_{l_i} > 1$)

7   **break**;

8 AdaptP();

Fig. 4. Algorithm CalcContribution()

illustrative example of coverage is shown in Fig. 3 (refer to Fig. 1 for the distribution of the sensors in this example).

We now identify the necessary long-term coverage contributions from the two types of sensors. Clearly, for grid i, $i = 0, 1, \ldots, n^2 - 1$, the contribution from a mobile sensor depends on the fraction of time that the mobile sensor will be present in this grid; in other words, the probability that it travels to the grid. We denote this probability by π_i for all mobile sensors. The contribution from a static sensor in the grid is equal to its activation probability: the higher this probability, the better the coverage will be.

We now focus on the optimal values of p and $\pi = [\pi_0, \pi_1, \ldots, \pi_{n^2-1}]$. In the next section, we will present a random walk model that achieves π.

To facilitate our discussion, we use $d(i)$ to represent the density of grid i, i.e., the number of static sensors in this grid. Let M be the number of mobile sensors in the network. Given coverage requirement ratio δ, the following formulation maximizes the network lifetime:

$$\text{minimize} \quad p$$

$$s.t. \quad \pi_0 + \pi_1 + \ldots + \pi_{n^2-1} \leq 1 \qquad (1)$$

$$(1-p)^{d(0)} \times (1 - \pi_0)^M \leq 1 - \delta \qquad (2)$$

$$(1-p)^{d(1)} \times (1 - \pi_1)^M \leq 1 - \delta \qquad (3)$$

$$\vdots$$

$$(1-p)^{d(n^2-1)} \times (1 - \pi_{n^2-1})^M \leq 1 - \delta \qquad (4)$$

where Eq. (1) gives the contribution constraint of each mobile sensor, and Eqs. (2) - (4) ensure the coverage ratio of the grids, i.e., if Eqs. (2) - (4) are satisfied, the overall expected coverage ratio is greater than δ.

We present algorithm CalcContribution() that solves this optimization problem (see Fig. 4). In CalcContribution(), we first invoke subroutine SortGrid() to sort the grids in ascending order of their densities. Let l_i represent the index of the grid with rank i after sorting, i.e., $d(l_0) \leq d(l_1) \leq \ldots \leq d(l_{n^2-1})$. We then search for $\mathcal{K}$, the rank after which the grids are dense enough to be covered by the static sensors only. We start searching for $\mathcal{K}$ from 0, and evaluate the p for the current setting of $\mathcal{K}$. If we can find a valid p and π_{l_i}, then we increase $\mathcal{K}$, until $\sum_{i=0}^{n^2-1} \pi_{l_i} > 1$ (intuitively, this says that the potential of the mobile sensors is fully exploited) or $\mathcal{K}$ reaches n^2. In this process, p is decreasing because additional assistance from the mobile sensors is introduced after each iteration (See line 3, $\mathcal{K}$ increases every iteration).

Note that p is a real number but $\mathcal{K}$ is discrete. Hence, after the above process terminates, we in fact have an upper-bound on p corresponding to $\mathcal{K} - 1$, and a lower-bound on p corresponding $\mathcal{K}$. To find the optimal and practical p, we invoke a subroutine AdaptP(), which performs a binary search for the p and adjusts π_{l_i} accordingly. The termination of this subroutine depends on the precision of p, which is usually a predefined value. In our experiments, the depth of the binary search is always smaller than a constant factor of four.

We see that p decreases the algorithm has exhausted all possible p, i.e., if there is a better p than the outcome of CalcContribution(), then this p must have been searched. Therefore, this algorithm provide an optimal allocation between the static sensors and mobile sensors. The complexity of this algorithm is N^2 where N represents the total number of grids; and it does not depend on the number of sensors. In practice, if the field is very large and there are too many grids, it may take a long time for a single mobile sensor to collect all the field information. In this case, we can first do a simple uniform partition of the field according to the number of mobile sensors and let each mobile sensor be responsible for the information collection in a subfield. As such, the initialization phase can be remarkably shortened.

V. A Random Walk Model for Mobile Sensors

In the previous section, we obtained π, the long-term coverage contribution by the mobile sensors to the grids. It remains to show a concrete mobility model that can achieve this distribution. To this end, we demonstrate a viable and yet simple random walk model in this section.

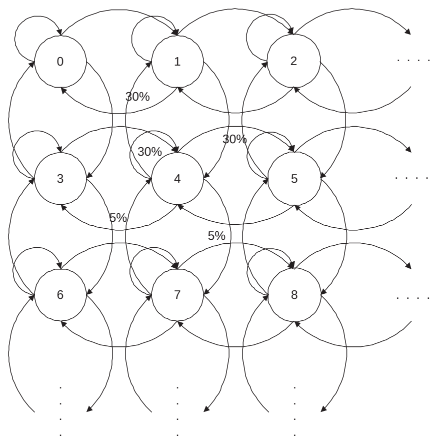


Fig. 5. Markov chain for the random walk model.

A. A Random Walk Model

In the random walk model, a mobile sensor will either stay in a grid, or move into an adjacent grid along four directions,[4] as shown in Fig. 2. We consider decisions depending only on the current grid where a mobile sensor resides. This results in a Markov chain where each grid is a state. We use P_{ij} to denote the transition probability from grid i to grid j. See Fig. 5 for an illustration. Given the long-run distribution π, this Markov chain obeys the following balance equations,

$$\pi_j = \sum_{k=0}^{n^2-1} \pi_k P_{kj}, \quad j = 0, 1, \ldots, n^2 - 1 \tag{5}$$

$$\sum_{k=0}^{n^2-1} \pi_k = 1 \tag{6}$$

$$\sum_{j=0}^{n^2-1} P_{kj} = 1, \quad \forall k \in [0, n^2 - 1] \tag{7}$$

$$0 \le P_{ij} \le 1, \quad \forall i, j \tag{8}$$

$$P_{ij} = 0, \quad \forall i, j, \text{ grids } i, j \text{ not adjacent} \tag{9}$$

where the first four equations are standard steady-state constraints for Markov chains [11], and Eq. (9) suggests that no transition is possible for two non-adjacent grids.

Our problem now is to determine the transition probabilities P_{ij} in this system of equations to reach the stationary distribution π. This is the inverse of the "given transition probability, find stationary distribution" problem in a Markov chain.

First of all, we need to ensure that the P_{ij} obtained can guarantee a limiting distribution π. By ergodic theorem [15], a Markov chain that is *aperiodic*, *irreducible* and *positive recurrent* has a limiting distribution[5]. Since there are only a finite number of states in our system, if our Markov chain is irreducible, it is positive recurrent. As such, if we ensure that the Markov chain is aperiodic and irreducible, it is sufficient to guarantee this π exists. For ease of discussion, we now assume that $\pi_k > 0$ for $k = 0, 1, \ldots, n^2 - 1$. We will generalize the solution later.

To ensure aperiodicity, we can set all the P_{ii} to be strictly positive. To ensure irreducibility, the mobile sensors cannot be trapped in a grid or a group of grids; hence, we have an additional set of constraints:

$$\forall i, \quad 0 < P_{ii} < 1, \tag{10}$$

which indicates that whenever a mobile sensor moves into a grid, the probability that it will stay in this grid should be strictly less than 1. A stronger condition is

$$P_{ij} > 0, \quad \forall i, j, \text{ grids } i, j \text{ are adjacent}, \tag{11}$$

which ensures that the mobile sensor always has chance to move into a neighboring grid. Eq. (8) can then be replaced by

$$0 < P_{ij} < 1, \quad \forall i, j \text{ that are adjacent} \tag{12}$$

It is not difficult to see that the above set of equations have multiple solutions. We now illustrate one solution set. Our strategy is to first find a set of solution to Eq. (5) and Eq. (6) and then try to satisfy all others. Notice that if $\pi_k P_{kj} = \pi_j P_{jk}$, Eq. (5) can be satisfied. We set $P_{kj} = \pi_j$ and $P_{jk} = \pi_k$ for all $P_{jk} \neq 0$ and $P_{kj} \neq 0$. This can always be achieved because either P_{kj} and P_{jk} are both strictly positive, or $P_{kj} = P_{jk} = 0$. We then set $P_{ii} = 1 - \sum_{j=0}^{n^2-1} P_{ij}$, and it is easy to verify that $P_{ii} > 0$. Therefore, Eqs. (5), (6) and (7), (9) are satisfied. Since $\pi_k, \pi_j \neq 0, 1$ we have $P_{jk}, P_{kj} \neq 0, 1$, and Eqs. (10), (12) are satisfied.

In summary, the solution set is

$$P_{jk} = \begin{cases} \pi_k & \forall j \neq k \text{ and } j, k \text{ are adjacent;} \\ 0 & \forall j \neq k \text{ and } j, k \text{ are not adjacent;} \end{cases} \tag{13}$$

$$P_{jj} = 1 - \sum_{k=0}^{n^2-1} P_{jk} \quad \forall j \neq k \tag{14}$$

Here we emphasize again that we assume $\pi_k > 0$ for $k = 0, 1, \ldots, n^2 - 1$. In section V.C, we will investigate an interesting impact of $\pi_k = 0$, i.e., that certain grids do not need assistance from the mobile sensors.

B. Boosting Movement

It is worth noting that the definition of coverage quality (Definition 1 in Section III.B) does not account for the moving frequency of the mobile sensors, nor the convergence time of the system. A *lazy movement*, where there is a high probability for the mobile sensors to stay in a grid, would achieve the same coverage ratio. An extreme example is one-time repositioning of the mobile sensors: a higher fraction of the sensor field can be covered, but the coverage could still be unbalanced or even with holes if the number of mobile sensors is not enough.

[4]In a boundary grid, a mobile sensor only have 3 or 2 directions to move.

[5]Aperiodic means that $P_{ii} > 0$. Irreducible means that all states are reachable from all other states. Positive recurrent means that the sensor will return to a state within finite time.

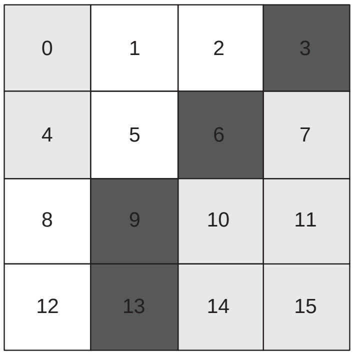


Fig. 6. Wall effect. Darker grids have denser static sensors.

Our random walk model can effectively solve this problem by adaptively setting the transition probabilities, allowing a wide range of movement frequencies. The strategy is to adjust the existing solution within the constraints to obtain another viable solution set. Specifically, to satisfy Eq. (5), we only need to have $\pi_k P_{kj} = \pi_j P_{jk}$; thus setting $P_{kj} = \alpha\pi_j$ and $P_{jk} = \alpha\pi_k$ also works given $\alpha > 0$. Let $\alpha_l, \alpha_u, \alpha_r, \alpha_d$ denote the adjustment factors for the four directions. To achieve a higher moving frequency, we can increase $\alpha_l, \alpha_u, \alpha_r, \alpha_d$, and the constraints will still be satisfied as long as the sum of the outgoing probabilities in a grid is less than 1. In our experiments, we set a threshold for P_{ii}: if a P_{ii} is greater than the threshold, we increase the α's until all P_{ii}'s are less than the threshold, or there is no possible further reduction. We call the scheme after this adjustment *aggressive movement*.

C. The Wall Effect and Solutions

We have assumed that π_i is non-zero in the previous Markov chain calculation. In practice, π_i can be zero for dense grids, i.e., those ranked higher than $\mathcal{K}$ in algorithm CalcContribution(). These grids will not get assistance from the mobile sensors and can simply be ignored in forming the Markov chain, if they are sparsely distributed. However, if a collection of such grids are connected, a *wall* can be formed, which partitions the field into two or more disjoint subfields. Given the presence of a wall (or multiple walls), a mobile sensor can not move freely in the whole field, and the expected distribution is no longer achievable. An example of this *wall effect* is shown in Fig. 6 where grids 3, 6, 9, 13 have dense static sensors and thus form a wall, splitting the fields into two subfields. Grid 0 and 4 also have dense static sensors, whereas they still need some assist from mobile sensors. We call them *semi-walls* as these grids make traveling in subfield (0, 1, 2, 4, 5, 8, 12) difficult, i.e., it may take a long time for the mobile sensors in grids 1, 2, 5 to reach grid 8, 12. As such, the coverage of the non-wall grids strongly depends on the initial placement of the mobile sensors, and a strategic allocation of the mobile sensors to the subfields is thus necessary.

1) Mobile Sensor Allocation for Subfields: Assume that, after invoking algorithm CalcContribution in the initial stage, the sensor field is divided into C subfields by walls. It is easy to see that the number of mobile sensors needed in each sub-field (excluding the wall grids) is independent of other subfields. We thus focus on a particular subfield, e.g., the kth one. Assume this subfield includes C^k grids, and similar to the notations used previously, let grid l_i^k be the ith rank in this subfield after sorting in ascending order of the densities, i.e., $d(l_0^k) \leq d(l_1^k) \leq \ldots \leq d(l_{C^k-1}^k)$. Let M^k be the number of mobile sensors to be assigned to this subfield. Our objective is to find the minimum M^k that provides the desired coverage for this subfield. This problem can be formulated as follows:

$$\text{minimize} \quad M^k$$

$$s.t. \quad \pi_{l_0^k} + \pi_{l_1^k} + \ldots + \pi_{l_{C^k-1}^k} \leq 1 \tag{15}$$

$$(1-p_{min})^{d(l_0^k)} \times (1-\pi_{l_0^k})^{M^k} \leq 1-\delta \tag{16}$$

$$(1-p_{min})^{d(l_1^k)} \times (1-\pi_{l_1^k})^{M^k} \leq 1-\delta \tag{17}$$

$$\vdots$$

$$(1-p_{min})^{d(l_{C^k-1}^k)} \times (1-\pi_{l_{C^k-1}^k})^{M^k} \leq 1-\delta \tag{18}$$

where p_{min} is the optimal value of p obtained in CalcContribution. To maximize the expected network lifetime, this value should still be identical for all the static sensors, even in the presence of subfields.

We can iteratively reduce M^k starting from $M - \sum_{j=0}^{k-1} M^j$. We allocate mobile sensors to each subfield one by one and, for the kth subfield, we start with the remaining mobile sensors after assigning all $k-1$ subfields. We then calculate the corresponding $\pi_{l_i^k}$ in each iteration. We stop until Eq. (15) is violated, (intuitively, this means that fewer sensors cannot provide necessary coverage). We thus obtain optimal M^k and $\pi_{l_i^k}$. Since the grids within the subfield all have $\pi_{l_i^k} > 0$, we can set the transition probabilities as before. The transition probabilities also guarantee that a mobile sensor will remain in its subfield during the random walk.

It is worth noting that after we calculate each M^k individually, it is possible that $\sum_{k=0}^{C} M^k > M$. This is because a sensor cannot be allocated fractionally. Given this negative impact of the walls, we need to increase p_{min} by decreasing $\mathcal{K}$; the contribution from the static sensors is thus increased. We continue until a $\mathcal{K}$ is found such that $\sum_{k=0}^{C} M^k \leq M$.

2) Subfield Partitioning: Besides the wall grids, other dense grids may have a very small π_i, implying that the mobile sensors should seldom visit them. Two examples are the grids 0 and 4 in Fig. 6. These two grids make a smooth walking in subfield (0, 1, 2, 4, 5, 8, 12) difficult and will significantly increase the convergence time of the system.

In the presence of semi-walls, we can further partition the subfields to balance the movement of the mobile sensors. Again, since the mobile sensors cannot be allocated fractionally, we have to strike a balance between the coverage and convergency. In our experiment, we set a threshold for the grids of semi-walls and show that the convergence time improves noticeably.

VI. Sensor Collaborations

So far we have established the respective contributions from static and mobile sensors, and the activation and movement strategies for them. This framework is easy to implement as it involves node interactions in the initial period only, and all the remaining operations are randomly and independently performed in a distributed fashion. Within this basic framework, various node interactions/collaborations could be introduced to further enhance the system performance. To show this, we now outline a simple yet effective node collaboration scheme.

The key observation is that by using a pure probabilistic model, there may be overlapping coverage of a grid by different sensors. To this end, we introduce a sensor collaboration protocol with two contention phases. We assume that time is partitioned into slots $[0, T_1]$, $[T_1, T_2]$, ..., $[T_i, T_{i+1}]$, ..., with slot length $T = T_{i+1} - T_i$. Without loss of generality, we consider the time slot starting at T_i. We have a contention interval $[T_i - t, T_i + t]$; where t is a fixed parameter such that $t \ll T$. The first phase $[T_i - t, T_i]$ is used for contention between mobile sensors to enter one certain grid. The second phase $[T_i, T_i + t]$ is used for suppressing multiple activation of the static sensors.

In $[T_i - t, T_i]$, mobile sensor m_j first decides which grid it will enter in the next time slot. Then, m_j randomly generates a number $t_j \in [0, t]$ and, at time $T_i - t_j$, sends a probe message to the sensors in the selected grid. If the grid has a mobile sensor or an active static sensor, it will allow m_j to enter in the next slot only if m_j is the first one sending the probe message. In $[T_i, T_i + t]$, each static sensor also generates $t_j \in [0, t]$, and, at time $T_i + t_j$, activates itself with probability p and broadcasts a probe message to its neighbors in the same grid. If a neighbor is a mobile or an already activated static sensor, it will reply by a reject message. The newly activated sensor thus has to deactivate itself to save energy.

VII. Performance Evaluation

In this section, we evaluate the performance of the hybrid sensor network in field coverage through simulations. We focus on the following typical measures: coverage quality, network lifetime, and convergence time.

In our simulation, we deploy 1000 static sensors in a field of 140m $\times$ 140m and the sensor field is partitioned into 100 virtual grids. The battery power for each sensor is 10000mAh, and can last for one day with persistent activation. We neglect the energy cost during dormant states.

We have examined the energy consumption status of the static sensors in our system. Fig. 7 shows the cumulative distribution curve of the residual energy after the death of the first sensor. We can see that at this time more than 70% of the sensors has residual energy less than 1000mAh (10% of the total energy reserve). It implies that the remaining operation time of the system is limited, and the lifetime of the first dead sensor serves as a legible measure for the system lifetime.

Unless otherwise specified, the following default parameters are used: The expected coverage quality is $\delta = 0.85$, and the length of each time slot is 1 minutes. Each point in our figures is the average of 100 independent experiments.

A. Contribution of Mobile Sensors

In first set of experiments, we deployed different number of mobile sensors in the field to observe their effectiveness. In Fig. 8, we show the network lifetime as a function of the number of mobile sensors. The number of mobile sensors varies from 20 to 60, which accounts for only a small portion of all the sensors. For comparison, we also plot the result with static sensors only; to ensure fairness, in this case, we deployed additional static sensors (the same amount as mobile sensors), which are equipped with extra-batteries to remain active throughout the experiments. In our figures, we use w/ MS, w/o MS to denote the experiments with or without mobile sensors; w/ C, w/o C to denote the experiments with or without using the sensor collaboration protocol.

We observe that the use of mobile sensors substantially increases the network lifetime. For example, consider the case where there are 50 mobile sensors, the lifetime (w/ MS, w/o C) is three times longer than without mobile sensors (w/o MS, w/o C). In addition, we see that the lifetime improves steadily when more mobile sensors are deployed. On the contrary, by adding a few static sensors only, there is no clear improvement of the system lifetime. Node collaboration also improves the life time for both cases, but more substantially if mobile sensors are used. The improvement percentage is plotted in Fig. 9. We can see that without mobile sensor (w/o MS, w/ C), there is a 10% to 20% lifetime improvement with sensor collaboration compared to without collaboration. If mobile sensors are used, this effect is much pronounced. This is because without mobile sensors, the lifetime is constrained by the grids with fewer sensors, resulting in smaller chance of suppressing redundant activations. Since node collaboration substantially improves the system performance, for the rest of our experiments, we will focus on the performance of the system with collaboration only.

We next consider the effect of two different distributions of the static sensors. First, we deployed the static sensors randomly and uniformly. Second, we added some bias on the distribution, where the right side of the sensor field was two times denser than the left side of the sensor field. Fig. 10 shows the comparison results. Not surprisingly, the lifetime has reduced in biased distribution as the system is more stressed. With assistance from mobile sensors, however, the situation improves fast; for example, with 20 mobile sensors, the lifetime is only marginally better than with no mobile sensors, whereas with 60 mobile sensors, the lifetime is less significantly affected by the biased distribution. This clearly shows the inherent adjustment capability of mobile sensors.

B. Convergence Time

We now consider the convergence time of the network, in particular, the effect of moving speed of the mobile sensors. We simulated 50 mobile sensors in the sensor field. In initialization, the whole sensor field was partitioned into subfields by walls. All mobile sensors belonging to the same subfield were dispatched to the grid with the highest index in this subfield. Fig. 11 shows the coverage quality over time for both aggressive and lazy movements. We see that if

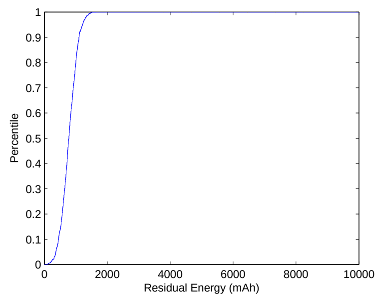


Fig. 7. Residual energy after the death of the first sensor.

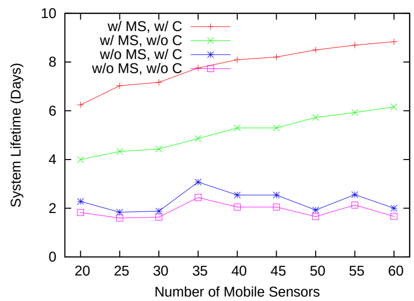


Fig. 8. Comparison of the system lifetime with and without mobile sensors, and with and without collaborations.

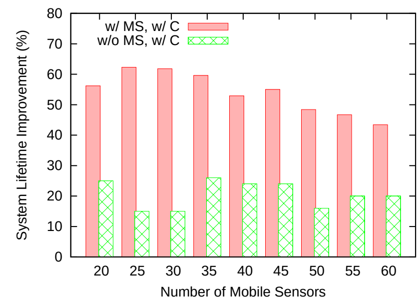


Fig. 9. System lifetime with or without collaborations.

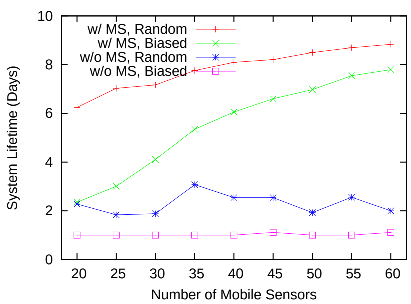


Fig. 10. Comparison of the system lifetime for uniform and biased distributions of static sensors.

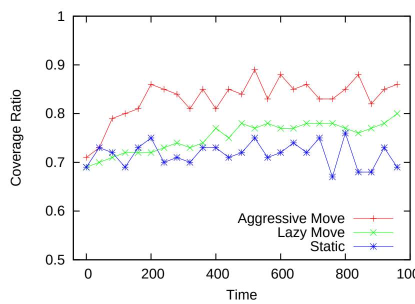


Fig. 11. Comparison of the coverage ratio as a function of running time for varying movement patterns.

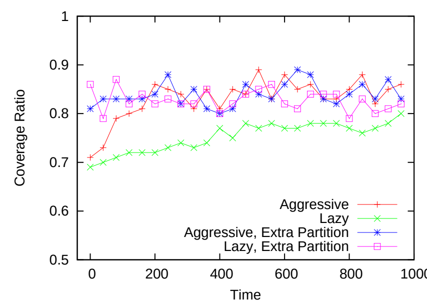


Fig. 12. Comparison of the coverage ratio as functions of running time with partitioning.

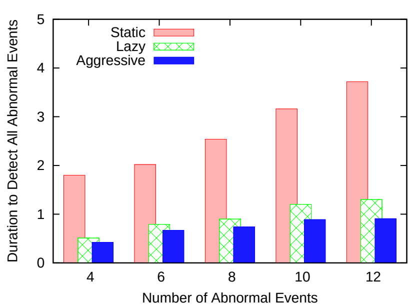
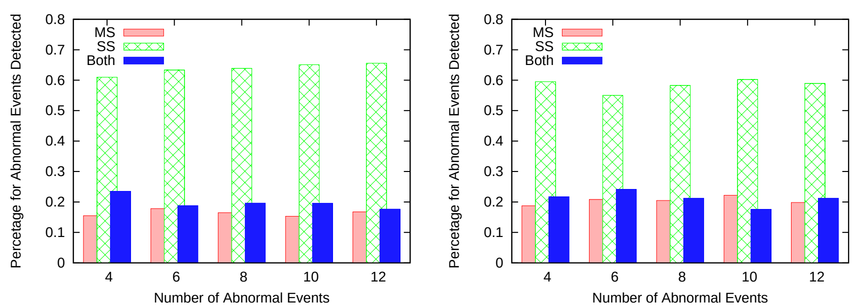


Fig. 13. Duration (seconds) to detect all abnormal events.



(a)

(b)

Fig. 14. Abnormal event detection. SS: Detected by static sensors only; MS: Detected by mobile sensors only; Both: Detected by both. (a) Mobile sensors with lazy movement. (b) Mobile sensors with aggressive movement.

there are high transition probabilities between adjacent grids, the convergence time is much smaller. For example, with aggressive movement, the system reaches 85% coverage after 200 minutes, while lazy movement has yet to reach this ratio after 1000 minutes. We can also see from Fig. 11, that the coverage ratio with static sensors only is only around 70%.

We consider the effect of finer partitioning of the subfields. From Fig. 12, we see that finer partition improves the convergence time with both aggressive and lazy movements.

These experiments clearly show that the walls and semi-walls in the field would remarkably affect the convergence of the system, and our allocation algorithms for the mobile sensors can effectively solve this problem.

C. Aggressive Movement in Event Detection

While finer partitioning makes the convergence time of lazy movement close to that of aggressive movement, we argue that aggressive movement can be much more effective than lazy movement in abnormal event detection.

We randomly generated abnormal events in the sensor field. In Fig. 13, we show the time needed to detect all these events for three strategies, namely, aggressive movement, lazy movement and without mobile sensors. Not surprisingly, the more abnormal events there are, the longer it takes to find all of them. We see that with aggressive movement, the detection time is not only shorter than the other two, but also increases more slowly when the number of abnormal events increases. The gain obtained from aggressive movement compared to lazy movement is around 5% to 15%. Notice that this is achieved neither by increasing the number of the mobile sensors nor by increasing their physical speeds, but simply by improving the transition probabilities between the grids. Finally, note that the detection time of using static sensors only is remarkably longer than the other two. In fact, in some tests, the events can never be fully detected if the grids has no any static sensor; we set an expiration time of 20 in such cases, which explains the high average detection time.

To further understand the contributions from static and mobile sensors, we show in Fig. 14 the ratio of the abnormal events detected by different types of sensors, namely, static, mobile, or both. We see that the static sensors are still the main source in coverage, detecting 55% to 60% of the abnormal events alone. This is not surprising consider the sheer number of the static sensors. The mobile sensors detect around 20% and for the other 20% cases, static and mobile sensors observe the abnormal events simultaneously. Again, this shows that a small number of mobile sensors can serve as an effective methods for field coverage. Fig. 14 (a) and (b) demonstrate the scenario where the mobile sensors adopt lazy movement and aggressive movement strategies. We can also see that, if aggressive movement is adopted, the mobile sensors become more effective in detecting abnormal events.

VIII. Conclusion

In this paper, we proposed a hybrid sensor network architecture, which consists of both static and mobile sensors for field coverage. We offered an optimal algorithm for calculating the coverage contributions, which fully explores the potentials of the mobile sensors and maximize the network lifetime. We further presented a random walk model for the mobile sensors. The model is low-overhead and fully distributed. Its parameters can be fine-tuned with different moving frequencies. As such, our model is general enough to match the moving capability of various mobile sensors and the demands from a broad spectrum of applications. We studied various extensions under this framework, such as the wall effect and in-network collaborations to further improves system performance.

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