Mobility-Assisted Sensor Networking for Field Coverage

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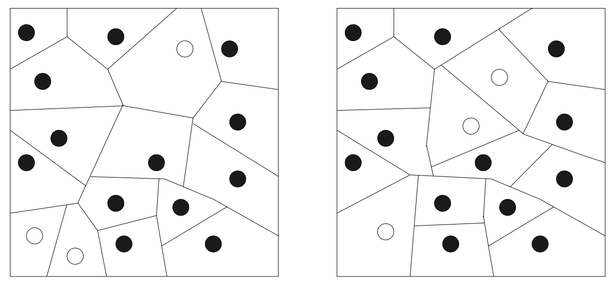
***Abstract*—In many sensor network applications, manual or well-controlled node deployment is not practical. Random deployments, e.g., from the air, often result in unevenly distributed nodes and hence insufficient coverage. In this paper, we present a novel mobility-assisted network for field coverage, and suggest that, by introducing only a small set of mobile sensors, the field coverage can be remarkably improved. The main challenges for this mobility-assisted framework are determining the necessary coverage contribution of the mobile sensors and achieving such contribution. We develop an optimal strategy for separating the contribution from static sensors and mobile sensors. We then proposed a random walk based mobility model for the mobile sensors to achieve their necessary contribution. We demonstrate through experiment that a small set of mobile sensors can effectively solve the unbalance of the sensor distribution and significantly improve the system lifetime and coverage quality.**

I. Introduction

Wireless sensor networks have been recently used for field protection and surveillance [3][12]. To accurately detect the abnormal events, a high quality coverage of the sensor field is necessary. In most previous studies, only static sensors are used. The quality of coverage is highly 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.

The advances in embedded systems and hardware designs have realized mobile sensors, such as Robomote [11] and Khapera [8]. 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 [5]. In other words, their lifetime is not bounded by the limited battery. A fully mobile sensor design was proposed in [7], where the sensors travels in a random walk fashion. While



(a) (b)

Fig. 1. Field coverage (a) before and (b) after reposition of the mobile sensors; black and white circles representing static and mobile sensors, respectively.

this theoretical result is exciting, the mobile sensors remain expensive nowadays. In addition, when all sensors are in random motion, packet routing and information dissemination will be much more complicated. We thus envision that a mobile sensor assisted network can be a cost-effective tool for coverage with unevenly distributed sensors. A related design was presented in [13], which suggested a one-time reposition of the mobile sensors after the initial deployment. An example of such design is illustrated in Fig. 1. The field is divided into a Voronoi Diagram and each sensor covers a cell. We can see that after reposition of the mobile sensors, the coverage is enhanced. Various other one-time reposition schemes can be found in [4][16]. This solution, however, proves inadequate for balancing the sensor coverage and load in many applications. First, after one-time reposition, the coverage of the field is still unbalanced, i.e., there are large and small cells. Second, in many applications, the sensing range of a sensor can not be fine tuned. Thus, in a dense network, the coverage capability of nearby sensors can be wasted.

In this paper we propose a mobility-assisted 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 an area, or their contribution for covering this area, 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 mobility-assisted network are, first, to clarify the necessary coverage contributions from the static and mobile sensors; and second, to find a

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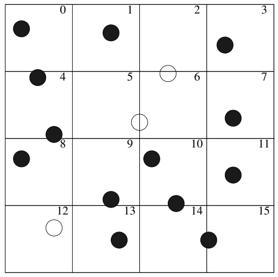

Fig. 2. Field covered by a mobile sensor assisted network; black and white circles representing static and mobile sensors, respectively.

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 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.

II. Mobility-Assisted Architecture

The network in our study consists of both static and mobile sensor nodes, which collectively monitor a field of interest. Similar to previous studies [2][15], 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 will show in Section IV that our analysis and algorithms can be easily extended to hexagon or other virtual structures. Through GPS or available positioning services [1], 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 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. Notice that the virtual grid size is determined by the sensing range. This is in contrast to [13], where the cell size of the Voronoi Diagram is determined by the distance of the neighboring sensors. 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. In our mobility-assisted network the mobile sensors are always active, and can stay in a grid or move to other grids. This feature can therefore assist with the covering of the holes in the field and reducing the load of the existing static sensors. An example of this grid structure is shown in Fig. 2.

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 [15].

In our framework, we adopt a random activation scheduling for the static sensors, and a random walk model for the mobile sensors. More specifically, our mobility-assisted sensor network goes through the following stages:

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

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.

III. Objective and Optimization

Since our main goal is covering related, we define a measure of how well a location is covered. Similar measurement is also used in [14].

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

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 [5]; 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 essentially suggests a load-balanced operation for the static sensors. Its effectiveness has been validated by our simulation results in Section V. 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.

We now identify the necessary long-term coverage contributions from the two types of 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. Clearly, to balance the workload, it is desirable to assign the static sensors with an identical activation probability p. The contribution from a mobile sensor for grid i, $i = 0, 1, \ldots, n^2 - 1$, 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.

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:

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

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

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

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

$$\vdots$$

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

where Eq. (1) gives the contribution constraint of each mobile sensor, and Eqs. (2) - (4) ensure the coverage ratio of the grids.

We present a heuristic for this problem. We see that the grid with the least number of static sensors should be assisted most; and we wish the static sensors in this grid to have a low activation probability p as the static sensors in dense grids. The mobile sensors, however, have an upper bound on contribution; as indicated in Eq. (1). Thus, we explore the capability of the mobile sensors iteratively following the density of different grids. Formally, let l_i represent the index of the grid in terms of density, i.e., $d(l_0) \leq d(l_1) \leq \ldots \leq d(l_{n^2-1})$. We then search for a key parameter $\mathcal{K}$, the index 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 $\mathcal{K}$ by $p = 1 - \sqrt[d(l_{\mathcal{K}})]{1-\delta}$. If, with this p, we can find a valid π_{l_i} that Eq. (1) is not violated, we increase index $\mathcal{K}$; 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.

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 can perform 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.

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.

IV. A Random Walk Mobility Model

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. There are many mobility models studied in literature; such as random walk, random waypoint walk, random trip, and fluid models. A survey and comparison of these models can be found in [10]. In this paper, we demonstrate that a viable and yet simple random walk model can successfully achieve our goal.

In the random walk model, a mobile sensor will either stay in a grid, or move into an adjacent grid along four directions[2]. We consider decisions depending only on the current grid of a mobile sensor. 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. Given the long-run distribution π, this Markov chain obeys the following balance equations,

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

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

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

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

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

where the first four equations are standard steady-state constraints for Markov chains [6], 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 [9], a Markov chain that is *aperiodic*, *irreducible* and *positive recurrent* has a limiting distribution[3]. 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

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

[3] 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.

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

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 $P_{jk} = \pi_i$ 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

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

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

In the above analysis we assume that $\pi_k > 0$ for $k = 0, 1, \ldots, n^2 - 1$. If $\pi_k = 0$, this indicates that the density of static sensors in grid k is high enough that grid k does not request assistance from the mobile sensors. These grids can simply be ignored by the mobile sensors unless they divide the entire sensor field into separate sub-regions. In this case we can allocate the mobile sensors appropriately into these regions and for each individual region, the calculation of the transition probability of the Markov chain remains unchanged.

A. Generalizing Grid Structure

We have assumed a square grid structure for the field in our study, which has also been widely adopted in this research area. A limitation of the square grid structure is its inflexible moving directions. As an example, consider an abnormal event is $R_m + d$ away from a mobile sensor, where R_m is the sensing range of a mobile sensor and d is a small distance. If the event happens in the upper-right direction (see Fig. 3 (a)), then because the two grids are not adjacent, the mobile sensor will detect it after moving at least twice. A hexagon structure, like that in the cellular network, will perform better in this case. As shown in Fig. 3 (b), only if the abnormal event is more than $2R_m$ away from the mobile sensor can it avoid being possibly detected in the next sensor movement.

Our mobility-assisted network and mobility models are not restricted to the square grid structure. They can easily accommodate the hexagon or even more general polygon structures. In fact, algorithm CalcContribution does not depend on the grid structure. Only some transitions are to be added in the Markov chain, e.g., for the hexagon structure, six transitions are needed against the four for the square grid case, and other calculations remain unchanged.

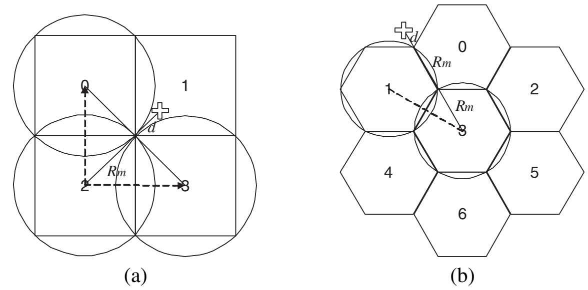

Fig. 3. Abnormal event is shown as a cross. (a) Grid structure. The mobile sensor in grid 2 has to move at least two steps to detect the abnormal event, which is only slightly more than R_m far away from the mobile sensor. (b) Hexagon structure. Only if the abnormal event is greater than $2R_m$ from the mobile sensor, can it avoid being possibly detected in next sensor movement.

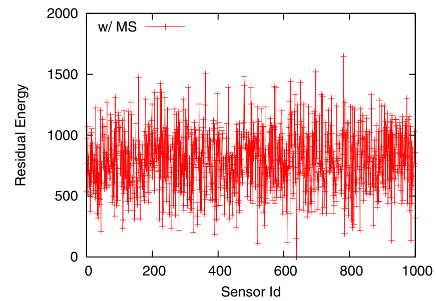

Fig. 4. Residual energy after the death of the first sensor.

V. Performance Evaluation

In this section, we evaluate the performance of the mobility-assisted sensor network in field coverage through simulations. We focus on coverage quality and network lifetime.

In our simulation, we deploy 1000 static sensors in a field of 140m × 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. 4 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. Simulation Results

In first set of experiments, we deployed different number of mobile sensors in the field to observe their effectiveness. In Fig. 5, 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.

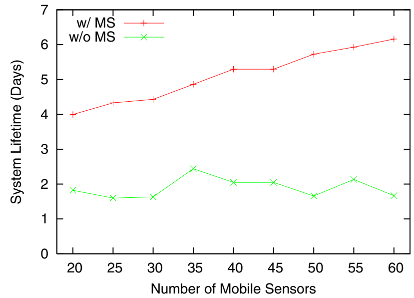

Fig. 5. Comparison of the system lifetime with and without mobile sensors, and with and without collaborations.

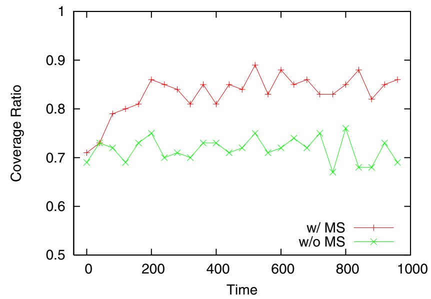

Fig. 6. Comparison of the coverage ratio as a function of running time for varying movement patterns.

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 is three times longer than without mobile sensors. In addition, we see that the lifetime improves steadily when more mobile sensors are deployed. On the contrary, by adding static sensors only, there is no clear improvement of the system lifetime. This clearly shows the inherent adjustment capability of mobile sensors.

We now consider the coverage ratio of the network. We simulated 50 mobile sensors in the sensor field. Fig. 6 shows the coverage quality over time given the same activation probability for the static sensors (so as to have the same system lifetime). We can see that the coverage ratio with mobile sensors steadily approaches 85% while without mobile sensors the coverage ratio is only around 70%.

To further understand the contributions from static and mobile sensors, we show in Fig. 7 the ratio of the abnormal events detected by different types of sensors, namely, static, mobile, or both. Abnormal events are randomly and uniformly generated from time to time. We see that the static sensors are the main source in coverage, detecting 55% to 60% of the abnormal events alone. The mobile sensors detect around 20% and for the other 20% cases, static and mobile sensors observe the abnormal events simultaneously. This, again, indicates that a small set of mobile sensors assists load balancing while the cheaper static sensors carries the main duty for field coverage.

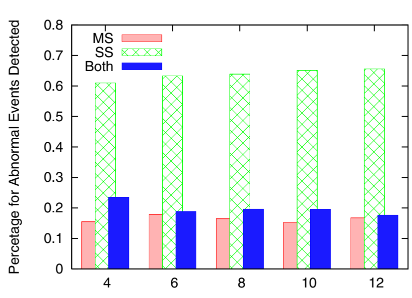

Fig. 7. Abnormal event detection. SS: Detected by static sensors only; MS: Detected by mobile sensors only; Both: Detected by both.

VI. Conclusion

In this paper, we proposed a mobility-assisted 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. Our model is low-overhead and fully distributed; further enhancement can also be incorporated.

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