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The Sink Node Placement and Performance Implication in Mobile Sensor Networks

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Abstract Mobile sensor networks are desirable in a variety of application scenarios, in which information collection is no doubt of great importance. In this paper, we present a mobile sensor network architecture consisting of a potentially large number of mobile sensors and a single or multiple stationary sink nodes for sensing information collection. We formulate a distinct coverage measurement problem in term of sensing information collection; we study the relevant performance and examine the effect from a variety of relevant factors through extensive simulations. We demonstrate that the performance is not only affected by the sensor mobility and the transmission range between mobile sensors and sink node(s), but also by the distribution of mobile sensors and the number and locations of sink nodes. Based on the observation and analysis, we also provide some preliminary understandings and implications for improving the information collection performance.

Keywords sink node placement · mobile sensor network · information coverage

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1 Introduction

Wireless sensor networks (WSNs) have been widely studied in recent years and are expected to be applied in a variety of application scenarios such as battlefield surveillance and event detections, hostile environment monitoring, and animal behavior understanding. In typical sensor networks, only static sensors are used, in which the performance of such systems such as field coverage, highly depends on the initial deployment of sensors across a geographic area (called the *region of interest*). Given uneven sensor distributions, some regions often remain uncovered. In addition, this can be explored by adversaries once they gain knowledge about the deployment strategy and sensing characteristics, uncovered path(s) can be found to render the static sensor networks ineffectual [1, 2].

Recent advances in robotics and low power embedded systems have made mobile sensors possible [1, 2], which is believed to be capable to construct mobile sensor networks [3]. In such networks, sensors are mounted by robots, animals or other moving objects, which can sense and collect relevant information. Mobile sensors can report sensing information to sink nodes within the coverage. The randomized mobility is appealing for several reasons: 1) there is no prior knowledge of the region of interest assumed [3]; 2) it would be difficult for an adversary or intruder to remain undetected [2, 3]; 3) perhaps more challenging in an unfriendly environment, mobile sensors may be not aware of the locations of sink nodes beforehand.

Among various aspects of challenges posed by such mobile sensor networks, the field coverage (or called area coverage) by mobile sensors has been studied [1–3]; the information collection (or called sensing data gathering) from mobile sensors, however, has not received adequate attentions. Specifically, how to capture the information collection of a mobile sensor network? What factors can affect the information collection performance? What effect and sensitivity from such factors? What is the implication? We believe it is important to understand the above questions in order to make a better use of mobile sensor networks for different application scenarios.

In this paper, we study the information collection performance and examine the effect from relevant factors in a mobile sensor network. Our main contributions in this study are: 1) We present a mobile sensor network architecture consisting of a potentially large number of mobile sensors with random walk and Gauss-Markov mobility, and a single or multiple stationary sink nodes collecting information from the mobile sensors; 2) we introduce and formulate a distinct coverage measure (in terms of distinct mobile sensors used to be collected by sink nodes over a period of time) to capture the information collection performance; 3) we show through extensive simulation that the information collection performance is not only affected by the sensor mobility and the transmission range between the mobile sensor and sink node, but also by the initial distribution of mobile sensors, as well as the number and locations of sink nodes. Further, we find that: 1) sensor mobility and the transmission range between the mobile sensor and sink node can be exploited to improve information collection performance, while they are constrained by the limited mobile speed and transmission capability of mobile sensor; 2) in order to obtain certain level of information collection performance, more sink nodes can be deployed to compensate for the limitation of sensor mobility and transmission range; 3) for grid and random initial distributions of mobile sensors, the placement of sink nodes should take into account the area boundary; 4) under the uneven initial distribution of mobile sensors, e.g., clustered distribution, the placement of sink nodes should consider the system-wide view of distribution of mobile sensors.

The rest of the paper is organized as follows. Section 2 reviews the relevant work. Section 3 presents basic system architecture, mobility model and coverage in term of sensing information collection. Section 4 provides simulation results and analysis. Section 5 concludes the paper with discussion on future work.

2 Related work

Recently, mobile sensor networks and relevant issues such as localization, mobility strategy, field coverage, and information collection, have received increasing attentions. Liu et al. [3] studied the dynamic aspects of the field coverage of a mobile sensor network that depends on the continuous movement of mobile sensors. Compared to static sensor networks, they showed that mobile sensors following a random walk can compensate for the lack of sensors and better field coverage. A more recent study on how the quality of field coverage scales with the motion velocity and strategies of mobile sensors can be found in [2]. Wang et al. [1][4] proposed a hybrid network of static sensors and mobile sensors with a random walk model and showed that a small set of mobile sensors can effectively address the uneven distribution of the static sensors so as to improve the field coverage quality. Zhang et al. [5] propose a range-free mobile inequality localization algorithm, which uses ring inequalities to restrict and estimate the possible location in numerical method. A comprehensive discussion on the mobility model including random walk, random waypoint, as well as Gauss-Markov can be found in [6].

The field coverage describes how well a region of interest is monitored by sensors; the coverage can have another interpretation from an information collection perspective. Lima et al. [7] introduced the *node coverage* to describe the sensing data gathering performance of a static sensor network with a single mobile patrol node in terms of the expected number of sensors captured within a given time frame. Shah et al. [8] utilized randomly moving "Data Mules" to help collect the sensing data. Kalpakis et al. [9] studied the problem of finding an efficient manner to collect data from all the sensors and transmit data to the base station, such that the system lifetime is maximized. There have been also studies on reliable and power-efficient data transmission and gathering [10, 11], on static sensor network with mobile sinks can be found in [12, 13], in which static sensors send out data when the sink is moving around.

The focus in this paper is different from all prior works in that we consider the information collection and relevant factors in a mobile sensor network composed of potentially large number of mobile sensors and stationary sink node(s).

We are particularly interested in the key factors that affect the performance of information collection.

3 System architecture

In this section, we present the basic system architecture, mobility model and coverage in term of sensing information collection.

3.1 The system model

We consider a mobile sensor network consisting of a potentially large number of mobile sensors (M). The mobility of sensor nodes follows a random walk model or Gauss-Markov mobility model within a 2-D geographic area A to sense the environment or detect events and store relevant information. There exists a single or multiple stationary sink nodes collecting information from the mobile sensors.

In order to capture the trajectory of the mobile sensor movement, the initial locations become relevant. Specifically, we assume that, at time t_0, the initial distribution $D(t_0)$ of mobile sensors across the area follows a certain pattern according to different application scenarios and requirements. In this study, we consider three typical initial distributions as follows:

- Grid distribution: mobile sensors are arranged using a grid-based fashion [14] across the area, and the separation between adjacent sensors is $\sqrt{|A|/M}$. The grid layout is a natural way for the cases in which it is possible and preferable to place the sensors in particular locations at the beginning.
- Random distribution: mobile sensors are randomly and independently distributed in the area. Such an initial deployment is suitable in scenarios where prior knowledge of the area is not available [3] or the area is not under control such as airdrop in an unfriendly area.
- Clustered distribution: mobile sensors are randomly distributed within single or several clusters of high density. This represents the uneven distributions.

Starting from one type of the initial distributions, in the first half of this paper, we assume that each mobile sensor performs the 2-D random walk movement, which is one of the most common and widely used mobility models [6]. With this mobility model, each mobile sensor travels from its current location to a new location by randomly choosing a direction $\theta\in[0, 2\pi)$ and a speed $v\in[v_{\min}, v_{\max}]$ respectively, in each discrete time interval Δt. We further make one simplification that all mobile sensors move at a constant speed $v=v_{\max}$, so that the distance traveled in each discrete time interval can be denoted by $r=v\Delta t$. This is reasonable for the application scenario in that each mobile sensor prefers to speed up its mission progress (e.g., searching a target in a vast area), and reports its information to the sink node as soon as possible; on the other hand, as pointed out in [3], more general speed distributions can be approximated using the fixed speed scenario. Depending on different types of mobiles and application context, sensors can have different levels of speed represented by r. For example, sensors can be mounted on robots or animals. We show in Section 4 that the information collection performance is very relevant to this factor.

A more realistic mobility model is considered in the second half of this paper: Gauss-Markov mobility model. This mobility model has been used for simulating mobile peer in PCS and ad hoc network [6]. It was used to adapt to different levels of randomness via tuning parameters. The mobility equation relates the current speed (S_n) and direction (d_n) of mobile peer with its pervious speed (S_{n-1}) and direction (d_{n-1}) in terms of tuning parameters α and b as shown in following equation:

$$s_n = as_{n-1} + (1-a)s \; + \sqrt{1-a^2}s_{x_{n-1}}$$

$$d_n = d_{n-1} + \sqrt{1-b^2}d_{x_{n-1}} \tag{1}$$

where $\bar{s}$ is the average speed of the mobile peers and the tuning parameters α and b are between 0 and 1. $s_{x_{n-1}}$ and $d_{x_{n-1}}$ are random variables from a Gaussian distribution. Compare with random walk model, the Gauss-Markov mobility model can eliminate the sudden stops and sharp turns by using the past velocities and directions to influence the future motion trajectory [6].

Besides mobile sensors, there exist a single or multiple stationary sink nodes $\{S_i\text{: } S_i\in A,\ 1\le i\le N\}$ for collecting information. Let the *transmission range* between a mobile sensor and the sink node R, i.e., each sink node is capable of communicating with or collecting information from those mobile sensors located within the disk of radius R centered at the sink node. Hence, once a mobile sensor entering the transmission region of a sink node, we say it is *covered*. Although we do not explicitly consider energy and storage constrains in this paper, the limited transmission range R can be viewed as energy constrain. For example, the commercially available sensors using ZigBee standards [15, 16] have the data transmission capability of 30 m~90 m in outdoor environment. We will show in Section 4 that different values of R can lead to different levels of information collection performance.

With limited transmission range, the sink nodes might not cover all the mobile sensors at specific time instants, but with the random walk mobility, more distinct mobile sensors can enter the transmission region of sink nodes to be collected over a period time $[t_0, t_0+T]$.

Table 1 summarizes the notations used in this paper.

Table 1 Notation

Symbols	Definitions
A	A vast 2-D geographic area called the region of interest (ROI)
M	The number of mobile sensors
$D(t_0)$	The initial distribution of mobile sensors across the area A
θ	The moving direction of mobile sensors, which is randomly chosen within [0, 2π)
v	The speed of mobile sensors, and in this paper we assume a constant speed
Δt	The discrete time interval in which each random walk movement occurs
r	The travel distance of mobile sensors at each Δt, which represents the speed. It depends on the mobile platform of sensors and r<<A
N	The number of sink nodes, and N≥1
S_i	The position of stationary sink node i, and S_i∈A, 1≤i≤N
R	The transmission range between the mobile sensor and the sink node
T	A period of time

3.2 Coverage from an information collection perspective

We now define the coverage measure from an information collection perspective as follows.

Definition 1 Coverage of distinct mobile sensors over a period of time T (denoted by *Coverage*(T)): The total number of distinct mobile sensors that enter the transmission region of stationary sink nodes (i.e., the information of mobile sensors is collected by the stationary sink nodes and the coverage count is increased) over a period of time $[t_0, t_0+T]$.

This coverage measure reflects the information collection in the sense that given a required time period, higher coverage value implies better collection; alternatively, in order to collect certain amount of information, the shorter time used to meet the requirement, the higher performance we could obtain.

We next use a simple case of single sink node to illustrate the factors affecting the coverage performance. At the beginning time t_0, suppose there are M_0 (≥0) mobile sensors already covered by the sink node due to the initial distribution $D(t_0)$. According to the Euclidean distance from the position of sink node, the remaining $(M - M_0)$ mobile sensors, which are initially outsides the transmission region of the sink node, can be classified to subsets of $\cup_i M_i$, where M_i denotes the set of mobile sensors that initially have the same Euclidean distance from the position of sink node, and

$$\sum_i M_i = M - M_0 \tag{2}$$

For any mobile sensor initially belonging to M_i, the possible location of the sensor at time $t_{j0}+j\Delta t$ can be characterized by the following normalized probability function:

$$\sum_{k=1}^{j} P(C_k, t_j) = P(C_1, t_j) + P(C_2, t_j) + \cdots + P(C_j, t_j) = 1. \tag{3}$$

Where those circle areas C_k (k≥1) denote the area of possible locations of the sensor as time goes by, as illustrated in Fig. 1. Note that at time t_j the farthest Euclidean distance traveled by the sensor cannot exceed C_j under the random walk mobility model. The probability term $P(C_k,t_j)$ is the probability of "the sensor lays within C_k at time t_j", and the exact probability density function is described in [16]. Thus, the probability of the mobile sensor to be covered by the

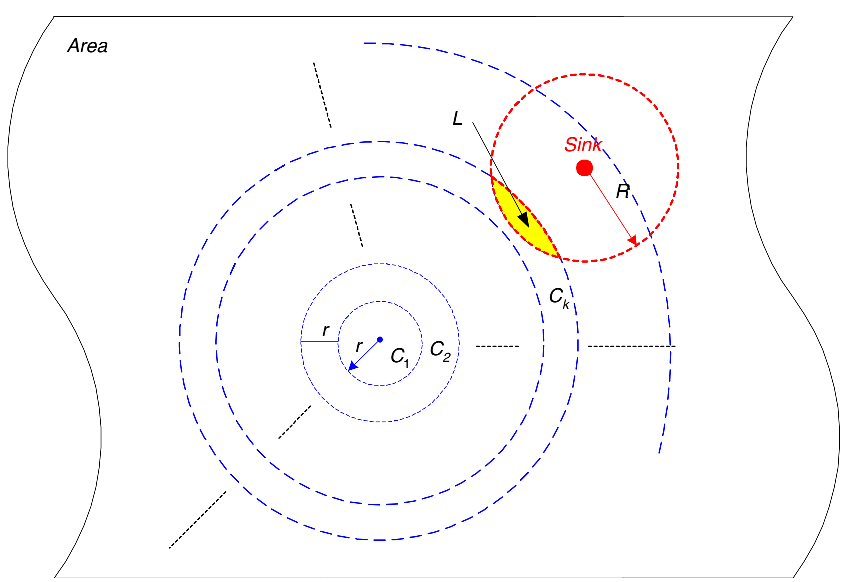


Fig. 1 A simple example for understanding the probability of a mobile sensor entering the transmission region of a sink node

transmission region of the sink node within a period of time $[t_0, t_0 + T]$ can be expressed as follows:

$$Q(M_i, T) \propto \sum_{j=i}^{T/\Delta t} P(C_i, t_j) \cdot L(C_i \cap S) + \sum_{j=i+1}^{T/\Delta t} P(C_{i+1}, t_j) \cdot L(C_{i+1} \cap S) + \cdots + \sum_{j=T/\Delta t}^{T/\Delta t} P(C_{T/\Delta t}, t_j) \cdot L(C_{T/\Delta t} \cap S). \quad (4)$$

Where the probability terms $L(C_k \cap S) \geq 0$ is related to the cross section area between the possible locations of mobile sensor and the transmission region of sink node, as shown in Fig 1.

Due to the symmetry, all the mobile sensors that initially belonging to the same M_i would have equal probability to be covered by the transmission region of the sink node. Therefore, the expectation of coverage over a period of time $[t_0, t_0 + T]$ can be expressed as follows:

$$E[Coverage(T)] = \sum_i M_i \cdot Q(M_i, T). \quad (5)$$

The above simple derivation reveals that the coverage performance is related to several factors. For example, the M_i are relevant to the number and initial distribution status of mobile sensors, as well as the position of sink node and the transmission range between mobile sensor and sink node; the possible locations of mobile sensor denoted by the C_k and so as the probability terms $Q(M_i, T)$ are relevant to the random walk movement of mobile sensors and the transmission range between mobile sensor and sink node, as well as the length of the time period.

4 Simulation and analysis

In this section, we first describe the simulation with relevant settings and then carry out a series of experiments to investigate the effect and sensitivity from various factors.

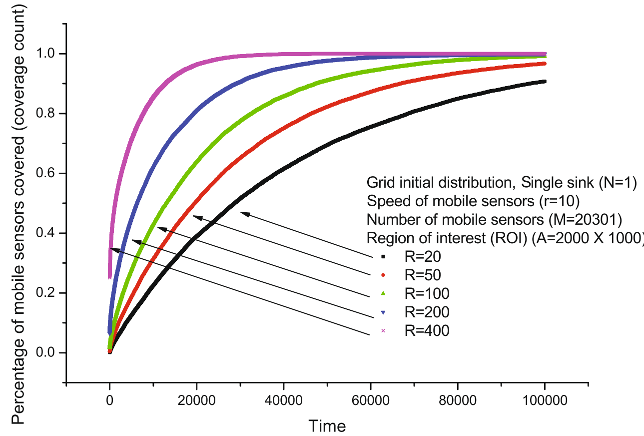


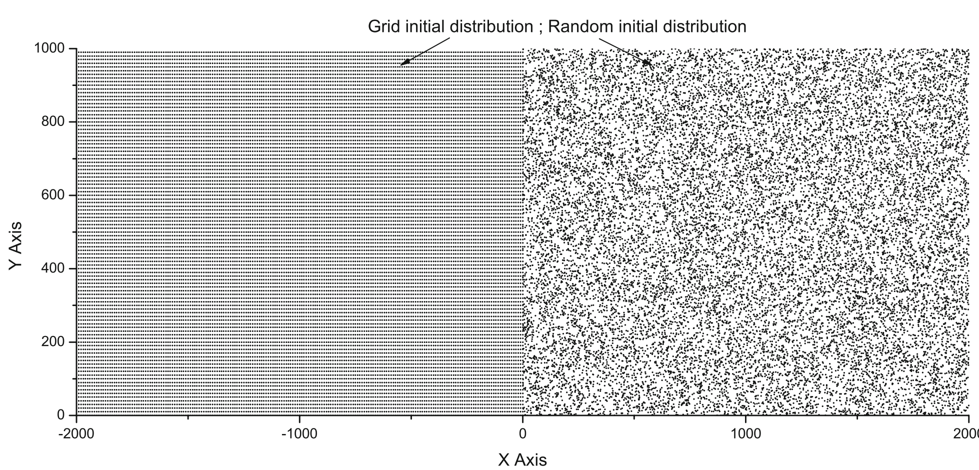
Fig. 3 Percentage of mobile sensors covered against time by varying the transmission range between mobile sensor and sink (R), beginning from grid distribution

4.1 Simulation setting

We develop a simulator that captures the essential aspects of the network and mobility model described in Section 3. Starting from a specific initial distribution of mobile sensors, the simulator continuously calculates the coverage measure along with distinct mobile sensors entering the transmission region of sink nodes over a period of time (T). Specifically, if a mobile sensor reaches the area boundary, it "bounces" off the area border according to the incoming direction [6].

Our simulator provides the flexibility of selectively controlling the configuration of various parameters including: 1) the length and width of the area ($l*w=|A|$); 2) the number of mobile sensors (M); 3) different types of initial distribution, e.g., grid, random and clustered distributions; 4) the speed of the mobile sensor (r); 5) the transmission range between mobile sensor and sink node (R); 6) the number ($N=1$ or $N>1$) and positions of sink nodes; 7) the length of the time period (T).

Fig. 2 Grid and random initial distribution



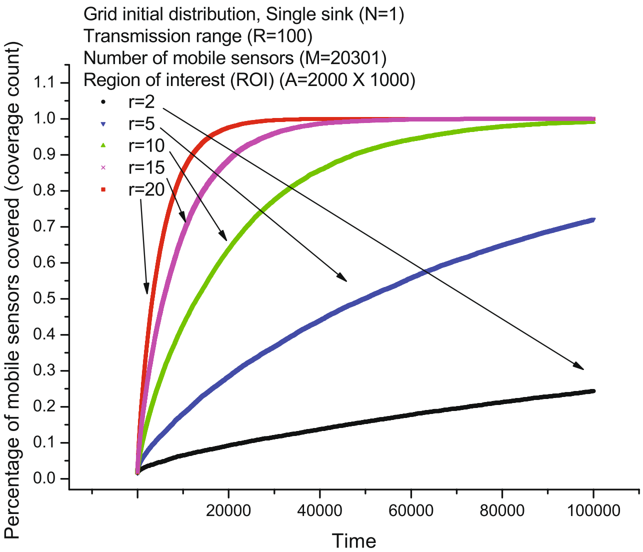


Fig. 4 Percentage of mobile sensors covered against time by varying the speed of mobile sensors (r), beginning from grid distribution

Unless otherwise specified, we use the following default settings: for grid distribution, we define the initial separation between adjacent sensors to be 10 units resulting in 20301 mobile sensors evenly distributed in an area of size 2000× 1000. For comparison, the same number of mobile sensors is used in random distribution and clustered distribution scenarios. The results are averaged over multiple runs for each corresponding set of parameter configuration.

4.2 Single sink

We first consider a single sink scenario with grid and random initial distributions of mobile sensors as shown in Fig. 2. We study the information collection performance by varying two important parameters: 1) the speed of mobile sensors (r) and 2) the transmission range between mobile sensor and sink node (R).

Figure 3 plots the percentage of mobile sensors covered against time by varying the transmission range between mobile sensor and sink node (R), beginning from grid initial distribution of mobile sensors. The figure shows five distinct increasing curves with different growth speed separated by transmission ranges from R=20 to 400 respectively[1]. The result demonstrates that the increase of the transmission range can sufficiently improve the information collection performance within a time period.

Figure 4 plots the percentage of mobile sensors covered against time by varying the speed of mobile sensors (r), beginning from grid initial distribution of mobile sensors. As we increase the parameter from r=2 to 20 respectively[1],

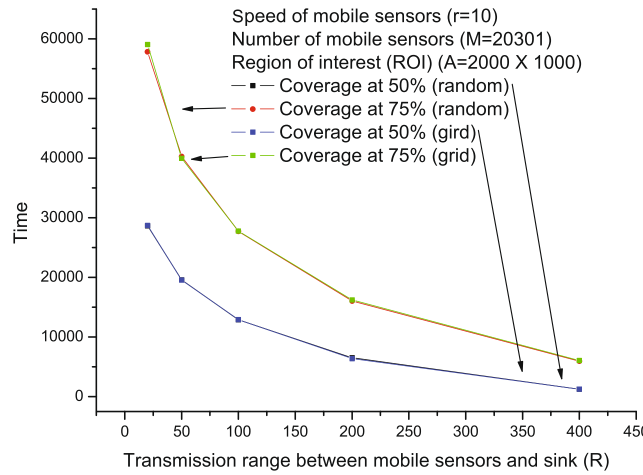


Fig. 5 Time to obtain 50% and 75% coverage against transmission range between mobile sensor and sink (R), beginning from grid and random distribution

the coverage curve rises sharply with high sensitivity, which means sensor mobility can significantly affect the information collection performance. This indicates that we can exploit the speed of mobile sensors to improve the information collection performance. Compared with Fig. 3, the parameter r has higher sensitivity than the parameter R.

Under a random initial distribution, we obtain similar conclusions that the increases of the values of R and r both result in increasing the coverage percentage within a fixed amount of time period, and r is more sensitive than R.

Figure 5 shows consistent results with that in Fig. 3, confirming that the increase of transmission range (R) can improve the information collection performance, i.e., reduce the time to reach certain level of coverage percentage. Specifically, under a fixed configuration of r and R, the time to achieve 75% coverage percentage is twice of the time to achieve 50%; it would take longer time to reach higher coverage percentage. Likewise, Fig. 6

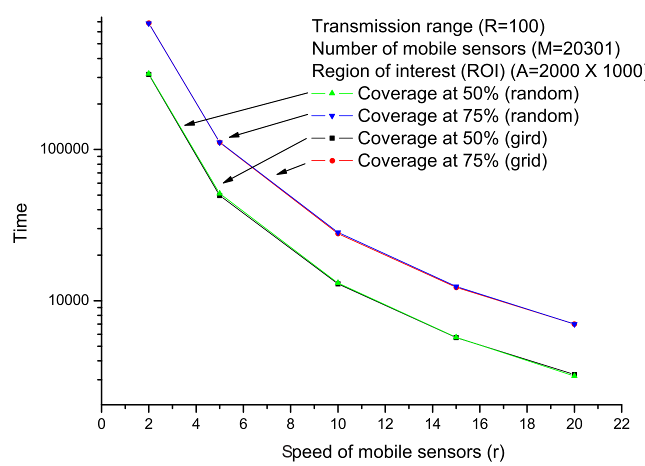


Fig. 6 Time to obtain 50% and 75% coverage against the speed of mobile sensors (r), beginning from grid and random distribution

[1] We choose the ratio between r, R and $|A|$ by considering their magnitudes in realistic situations [15, 16].

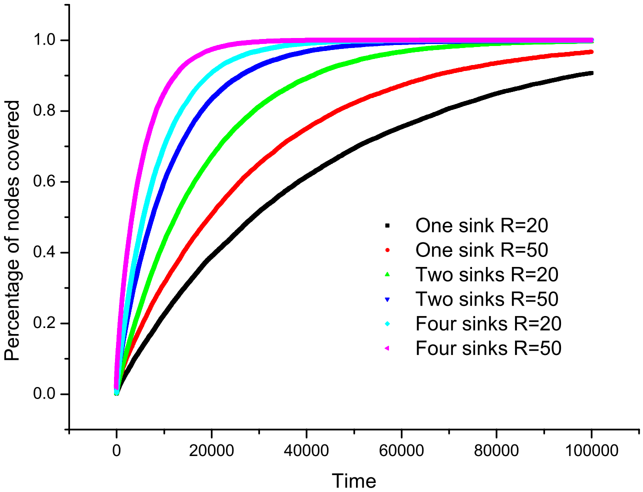


Fig. 7 Percentage of mobile sensors covered against time, comparison with one, two, and four sinks by varying the transmission range between mobile sensor and sink (R)

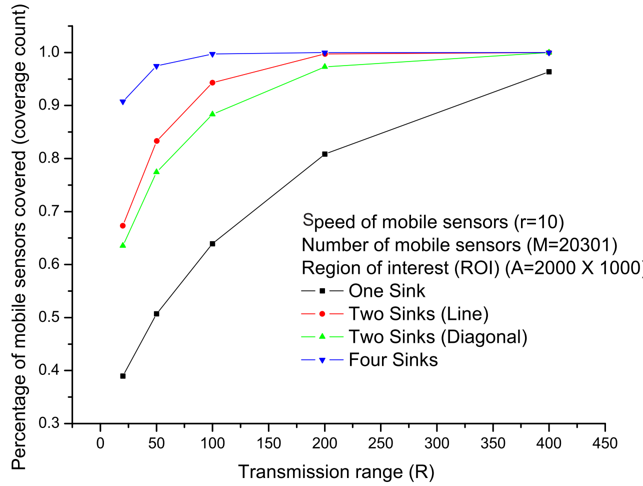


Fig. 9 Percentage of mobile sensors covered against transmission range (R), at a particular time (t=20000)

shows consistent results with that in Fig. 4, confirming that increasing the speed of mobile sensors (r) can improve the information collection performance.

In summary, for both of the grid and random distributions, increasing the speed of mobile sensors (r) and the transmission range between mobile sensor and sink node (R) can help to improve the information collection performance. However, since r and R represent the mobile platform speed and transmission capability of mobile sensor respectively, they are both constrained in realistic applications. For example, the commercially available sensors using ZigBee standards [15, 16] have a limited data transmission capability of 30 m~90 m in outdoor environment, and the Bluetooth standards [16] has even shorter transmission range; on the other hand, the speed of mobile sensor depends on the speed limitation of different types of mobile platform, such as robots or different kinds of animals.

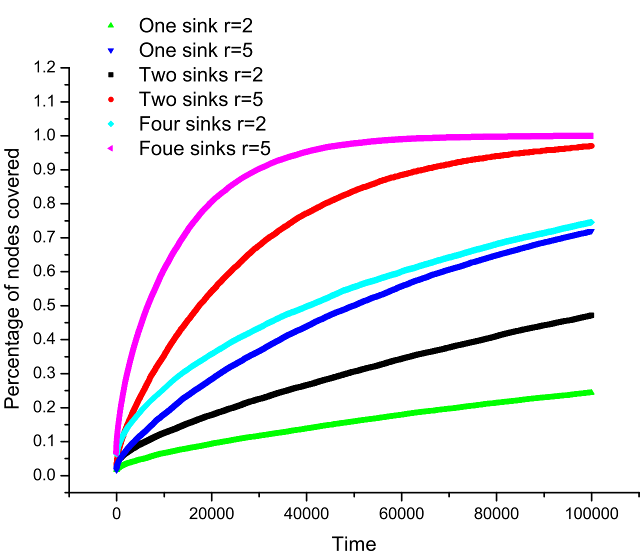


Fig. 8 Percentage of mobile sensors covered against time, comparison with one, two, and four sinks by varying the speed of mobile sensors (r)

4.3 Multiple sinks

In this subsection, we consider the multiple sink nodes scenario with grid and random initial distributions of mobile sensors. Specifically, we use the following sink nodes placement: (a) two sink nodes with *line* placement, i.e., at coordinates (500, 500) and (1500, 500); (b) two sink nodes with *diagonal* placement, i.e., at (500, 250), (1500, 750); (c) four sink nodes with *square* placement, i.e., at (500, 250), (500, 750), (1500, 250), and (1500, 750), respectively.

For grid initial distribution, Figs. 7 and 8 plot the percentage of mobile sensors covered against time for one, two (with *line* placement) and four sink nodes; further, Figs. 9 and 10 plot the percentage of mobile sensors

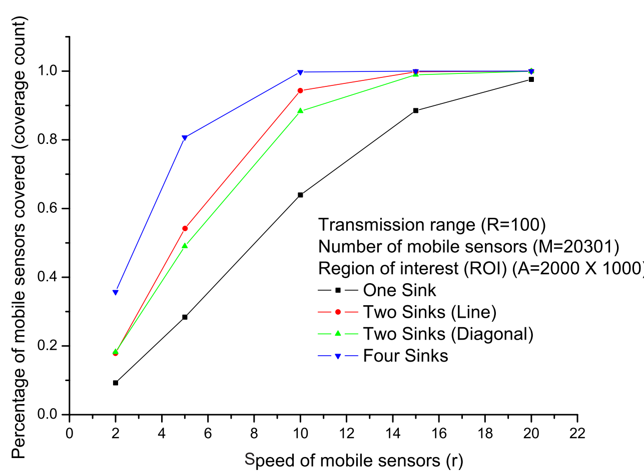


Fig. 10 Percentage of mobile sensors covered against the speed of mobile sensors (r), at a particular time (t=20000)

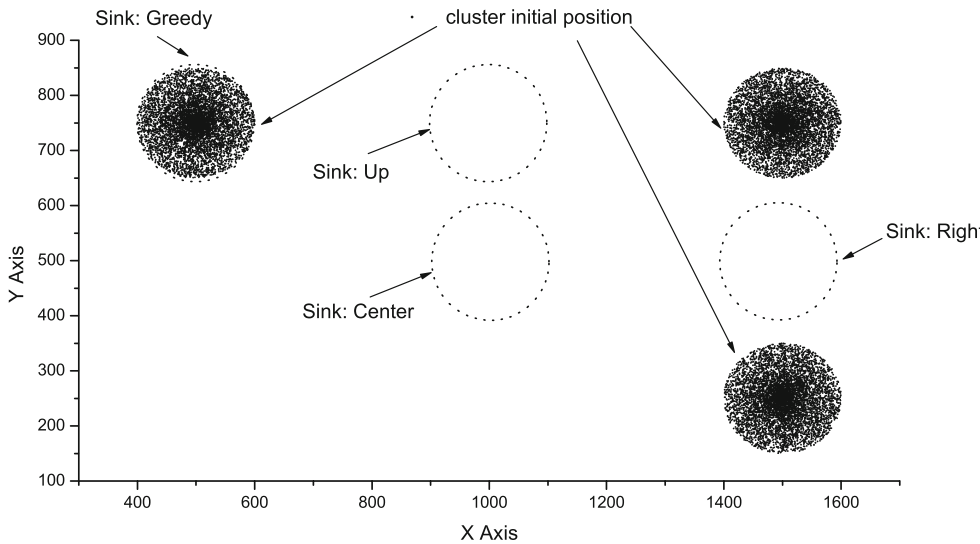


Fig. 11 Three-clustered initial distribution of mobile sensors, with four candidate sink node positions

covered against transmission range (R) and the speed of mobile sensor (r) respectively, at a particular time (t= 20000) when the percentage gap between single and multiple sink nodes clearly shown.

First, similar to single sink node scenario, the information collection performance with multiple sink nodes can be improved with the increase of R and r.

Second, increasing the number of sink nodes (N) can improve the information collection performance, which indicates that if r or R is constrained by a specific value due to physical limitation or application requirement. In order to achieve certain level of information collection performance, alternatively we can utilize more sink nodes to compensate for the limitation of r or R.

Third, the placement of sink nodes can greatly affect the information collection performance. For example, the coverage curve of two sink nodes with *line* placement outperforms the two sink nodes with *diagonal* placement. This is because the latter is relatively closer to the area boundary; this leads to unbalanced distribution of mobile sensors around the sink and cause more sensors to travel longer distance to be covered by the sink (i.e., less probability of being covered within a given period of time under random walk mobility model).

Similar results are observed under random distribution.

4.4 Clustered distribution

In this subsection, we illustrate the information collection performance for clustered initial distribution, by varying the number and placement of sink nodes.

As shown in Fig. 11, there are three clusters of mobile sensors which centered at coordinates (500, 750), (1500, 250), and (1500, 750), respectively. Each cluster has 6767 mobile sensors (i.e., the total number of mobile sensors is still 20301) distributed within a disk of equal radius.

We are interested in four candidate positions for placing a single sink node: "*Center* (1000, 500)", "*Up* (1000, 750)", "*Right* (1500, 500)", and "*Greedy* (500, 750) or (1500, 750)". By "*Greedy*", we mean that the sink node is placed at one of the cluster centers, so that a whole cluster of mobile sensors is immediately covered at the beginning.

Figure 12 plots the percentage of mobile sensors covered against time for different single sink node placements with a fixed setting of r and R. We find that the information collection performance of the *Right* placement outperforms the *Center* and *Up* placements by showing fast ramping speed at the beginning. Intuitively, the *Right* placement has a shorter distance with two clusters compared with the other placements as shown in Fig. 11. Hence, by equation (4), the

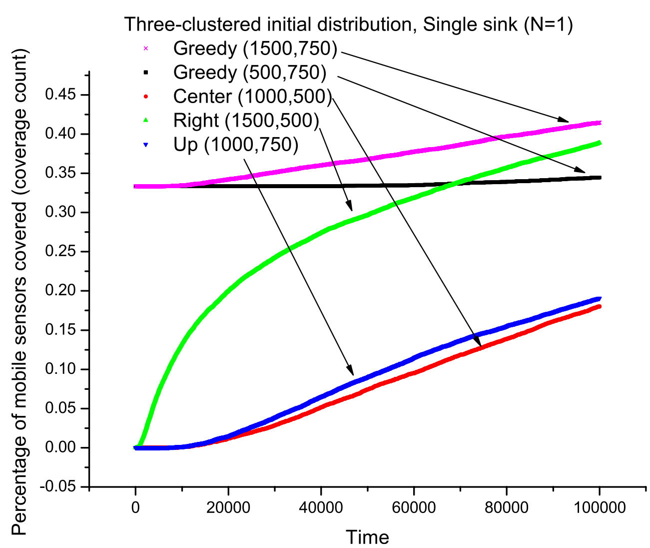


Fig. 12 Percentage of mobile sensors covered against time for different single sink node placements, beginning from three-clustered distribution

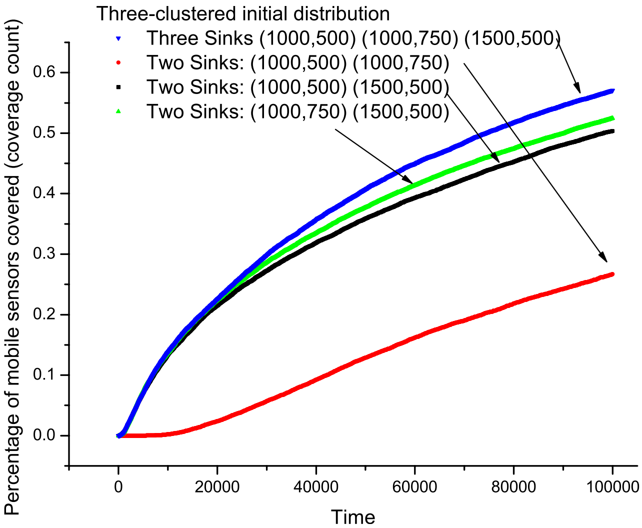


Fig. 13 Percentage of mobile sensors covered against time for multiple sink nodes placement, beginning from three-clustered distribution

$L(C_k \cap S)$ increases the probability $Q(M_i, T)$ within relatively shorter time period under *Right* placement, which leads to better information collection performance. Due to the similar reason, the information collection performance of *Greedy* (1500, 750) placement is better than *Greedy* (500, 750).

Although the initial coverage percentage of *Greedy* placement is much higher than the other placements at the beginning, the *Greedy* (500, 750) shows extremely slight increment as time goes by, and more interestingly, its corresponding curve is caught up by the *Right* placement. This indicates that in order to obtain higher information collection performance in a long term run, we should consider the system-wide view of distribution of mobile sensors for sink node placement.

Figure 13 plots the percentage of mobile sensors covered against time for multiple sink nodes placement with a fixed setting of r and R. For two sink nodes, the placement settings {*Up* (1000, 750), *Right* (1500, 500)} and {*Center* (1000, 500), *Right* (1500, 500)} show better information collection performance than the {*Center* (1000, 500), *Up* (1000, 750)}. This is due to the former placement settings contain the *Right* sink node placement, which shows much better information collection performance than the *Center* and *Up* placements, as already shown in Fig. 12.

Finally, the sink node number is increased to three with placement setting: {*Up*, *Right*, and *Center*}. From Fig. 13, the information collection performance of three sink nodes is not much better than two sink nodes. Again, this indicates that the system-wide view of distribution of mobile sensors plays an important role for sink node placement.

4.5 Gauss-Markov mobility

In this subsection, we change the mobile sensor mobility model from random walk to Gauss-Markov model, while keeping other simulation settings unchanged. We would like to demonstrate the information collection performances under different sensing mobility model.

First we compare the moving trajectory between random walk and Gauss-Markov mobility model (a=0.99, b=0.75) both in 1000 time steps and sensor speed (r)=2. Figure 14 shows that the mobile sensor with random walk movement can cover an area with 60×60 after 1000 time steps; while sensor with Gauss-Markov model can cover an area over 300×450. From the figure, less sudden stops and sharp turns appear in the Gauss-Markov mobility model, and due to this reason the sensor can travel longer distance within given time steps.

Simulation results with different sensor speeds are further examined in Fig. 15. Similar to the results from previous subsection, the information collection performance with Gauss-Markov mobility model can be improved with the increase of r. However, the information

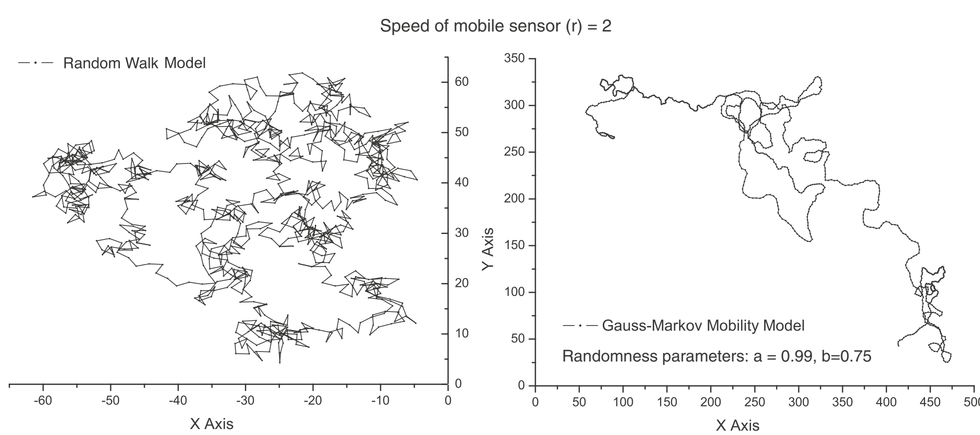


Fig. 14 Mobile sensor moving trajectory comparison between random walk and Gauss-Markov mobility model with 1000 time steps

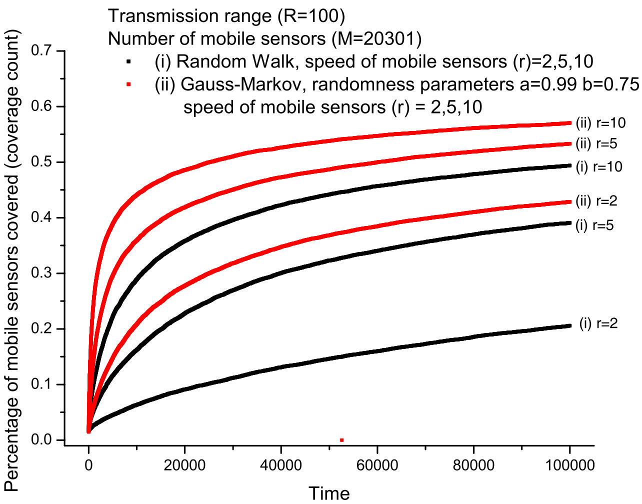


Fig. 15 Percentage of mobile sensors covered against time for random walk and Gauss-Markov mobility model with r=2,5,10

collection performance under Gauss-Markov model outperforms random walk movement by setting the randomness parameters as a=0.99, b=0.75. As shown Fig. 14, the Gauss-Markov model can cover larger area than random walk, and this give us an idea why the Gauss-Markov model can obtain better performance than random walk.

Figure 16 studies the information collection performance under the Gauss-Markov model with different randomness parameter settings. Since the effect of changing mobile sensor speed (i.e. randomness parameter a) is already studied in previous subsection, here we mainly vary the randomness parameter of direction (b). The result shows a comparison from b=0.00 to 0.95 and random walk motion. The information collection performance decreases with the increase of directional randomness, which consists with results in Fig. 15.

Finally, we try to study the effect of area boundary in terms of information collection performance. Originally, if a mobile sensor reaches the area boundary, it "bounces" off the area border according to the incoming direction. Intuitively, the *bounded* area restraints mobile sensor activities and the sink node can obtain higher information collection performance than *unbounded* case. Figure 17 illustrates the comparison between bounded and unbounded areas under different mobility models and proves the statement.

5 Conclusion and future work

In this paper, we present a mobile sensor network architecture composed of a potentially large number of mobile sensors with random walk and Gauss-Markov mobility, and a single or multiple stationary sink nodes collecting information from the mobile sensors. To describe the information collection performance of such a mobile sensor network, we introduced and formulated a distinct coverage measure in term of sensing information collection. We demonstrated through extensive simulation that the information collection performance is not only affected by the sensor mobility and the transmission range between the mobile sensor and sink node, but also by the initial distribution of mobile sensors, as well as the number and locations of sink nodes.

There are several avenues for further studies: 1) to consider different mobility models such as the one [5]; 2) to study the relationship between the field coverage and the

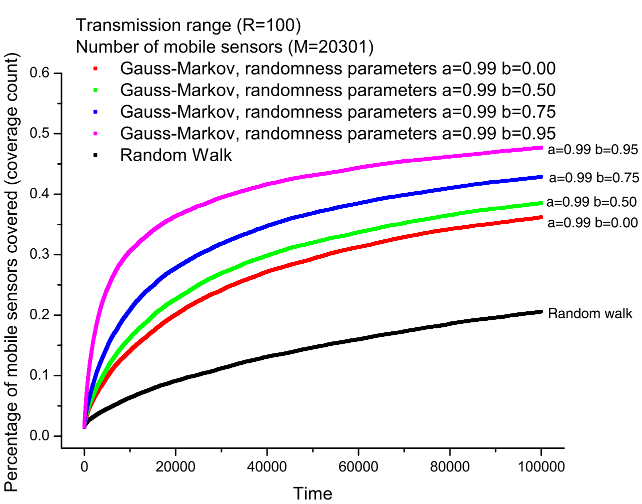


Fig. 16 Percentage of mobile sensors covered against time for Gauss-Markov mobility model with different randomness parameter settings

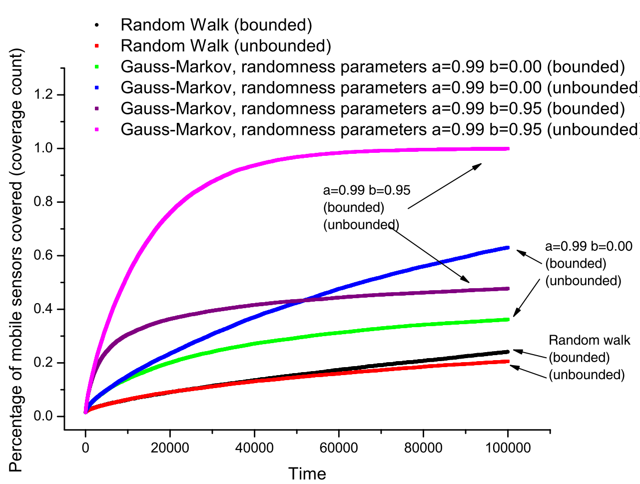


Fig. 17 Percentage of mobile sensors covered against time for bounded and unbounded areas with different mobility models

coverage in term of sensing information collection; 3) sink node placement strategy for certain sensor distribution and mobility; 4) consider other initial sensor distributions, more realistic area shapes and situations (e.g., with obstructions).

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