Trade-off Between Mobile Node Density and the Detection Performance in Mobility-Assisted Sensor Networks

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***Abstract*—In this paper, stationary target detection in a hybrid sensor network consisting of both static and mobile nodes is considered with random node mobility models. Static nodes and mobile nodes (initially) are assumed to be deployed independently and randomly in the sensing field. Mobile nodes are exploited to compensate for the lack of coverage provided by static nodes, and subsequently a time varying coverage improvement is achieved. We evaluate the detection performance of the hybrid network analytically based on geometric probability. We consider two sensing models: single-sensing detection and multiple-sensing detection. We characterize the trade-off between the mobile node density and the detection performance in terms of network parameters, with an expense of a certain delay constraint. Results presented in this paper give insights on selecting mobile node density in designing hybrid networks consisting of both static and mobile nodes in order to reach a desired performance requirement. Validity of the derived analytical results is verified via Monte-Carlo simulations.**

I. INTRODUCTION

In this paper we consider the problem of detecting a stationary target using a hybrid sensor network consisting of both mobile and static nodes. We assume that the static nodes and the initial locations of mobile nodes are both independently and uniformly distributed in a two dimensional plane such that initial node locations follow a 2-D Poisson point process. Such a deployment model for the nodes can be justified in situations where the network does not have any prior information regarding the sensing field and the target locations, or when it is more cost effective and practical to deploy nodes randomly in contrast to systematic deployment. We further assume that mobile nodes move randomly and independently in the sensing region searching for targets. Random and independent mobility models are desirable when nodes do not have prior information on target existence and are easily implementable since they require minimum coordination among mobile nodes.

We consider two detection models: single-sensing and k-sensing [1]. In single-sensing detection, the target is assumed to be detected if at least one sensor detects it providing the minimum guarantee of detection [1]. In k-sensing detection, on the other hand, the target is assumed to be detected if at least k-sensors detect it where k is a design parameter. In this model, the target is detected with lower false alarm probability than with single-sensing detection [1]. Mobile nodes are assumed to move independently and randomly in the sensing region. We consider two specific random mobility models: In the first model we assume that each mobile node initially selects a direction randomly and uniformly from $[0, 2\pi)$ and then move on a straight line in the selected direction [2]. In the second model, the mobile nodes are assumed to follow 2-dimensional random walks [3].

Under these detection and node mobility models, the detection performance of the hybrid sensor network is analyzed for detecting a stationary target. Specifically, we derive analytical results that help selecting parameter values in designing hybrid sensor networks for target detection. For example, since deploying mobile nodes in a network can be more expensive than deploying static nodes, it is important to deploy the minimum required number of mobile nodes in order to reach a desired performance level within a desired delay constraint. We characterize this minimum mobile node density required in order to achieve a desired performance level within a given delay constraint analytically.

The paper is organized as follows: In Section II, we present related work. Section III explains the sensor network, target and detection models. Section IV derives the detection performance of stationary target detection with single-sensing and k-sensing detection models and discusses its dependence on mobile node density. Performance results are shown in Section V and final concluding remarks are given in Section VI.

II. RELATED WORK

Distributed detection in wireless sensor networks with stationary sensor nodes has been extensively studied by many authors in the literature. For example, in [4]–[8], decision fusion for distributed detection was considered in different contexts when the sensor nodes are located at fixed positions.

In practice, random sensor deployment for sensor networks is desirable in many situations. For example, if a priori knowledge of the sensing field is not available at the deployment stage, it is more desirable to position sensors randomly. Moreover, random sensor deployment is justifiable when it is more cost effective and practical to deploy nodes randomly in contrast to systematic deployment. Stationary and mobile target detection in random stationary sensor networks has been studied by [1], [9], [10]. Since the performance of such a stationary sensor network is limited by its initial configuration, recently mobile sensor nodes are deployed in wireless sensor network applications to provide dynamic on-demand system performance. Use of node mobility at deployment stage to provide a uniform coverage by node relocation was considered in [11], [12]. However, these studies do not provide a performance improvement on-demand after deployment stage. Liu et. al. in [2] showed that the coverage can be improved by allowing nodes to be mobile continuously in a mobile sensor network over time compared to that with a static network. However, deploying mobile sensor nodes is not as cost effective as deploying static nodes in a sensor network due to energy constraints. Thus it is desirable to allow only a fraction of total nodes to be mobile to improve the system performance depending on application requirements. Motivated by these, in this paper we address the problem of detecting an arbitrary target located independently and randomly in a hybrid sensor network consisting of both static and mobile nodes.

III. System Model

We consider a hybrid sensor network made of N total sensor nodes deployed in a region $\mathcal{R}$. We assume that there are N_s number of static nodes and N_m number of mobile nodes. Denote (x_{sk}, y_{sk}) to be the location of the k-th static node where x_{sk} and y_{sk} are assumed to be independently and uniformly distributed in $[-b/2, b/2]$ where $b \times b$ is the assumed dimension of the sensor network. Note that we assume that the total number of sensor nodes N and network dimension $b \times b$ are large enough so that assumptions made in the rest of the paper are valid. Denote $\lambda = \frac{N}{b^2}$ to be spatial density of the nodes and $\lambda_m = \frac{N_m}{N}$ and $\lambda_s = \frac{N_s}{N}$ to be the fractions of mobile and static nodes respectively. Let $\mathcal{V}$ be the set containing all node indices in the network and let $\mathcal{V}_m$ and $\mathcal{V}_s$ be the sets containing mobile and static node indices, respectively. We consider stationary target detection by the hybrid sensor network, where the target location is assumed to be an independently and uniformly distributed arbitrary point P_0 in the region $\mathcal{R}$.

A. Node mobility models

In this paper, we consider two random mobility models: In the first model (model 1), each mobile node moves independently in a direction θ selected randomly and uniformly where $\theta \sim \mathcal{U}[0, 2\pi)$, with an average speed of $\bar{v}$ which is assumed to be the same for all mobile nodes. Note that we use $X \sim \mathcal{U}[a_1, a_2]$ to denote that X is uniformly distributed in the interval $[a_1, a_2]$. Then at any time $t = nT_s$, a mobile node has moved on a straight line a distance of $n\bar{v}T_s$ where T_s is the length of each time step [2]. Second, in model 2, we consider that k-th mobile node follows a 2-dimensional random walk [3] of n steps at time nT_s with each of a length $\mu = \bar{v}T_s$. Random and independent mobility models are justifiable in scenarios where nodes do not have any prior knowledge of sensing field or target existence. Also random node mobility models are desirable when minimum node coordination is required. Model 1 assumed in the paper is the simplest mobility model which requires minimum control and coordination. Random walk mobility model can be justifiable when mobile nodes are characterized by uncontrolled dynamics, such as random ON-OFF transitions at each time step [13]. These two random models for a mobile node are illustrated in Fig. 1.

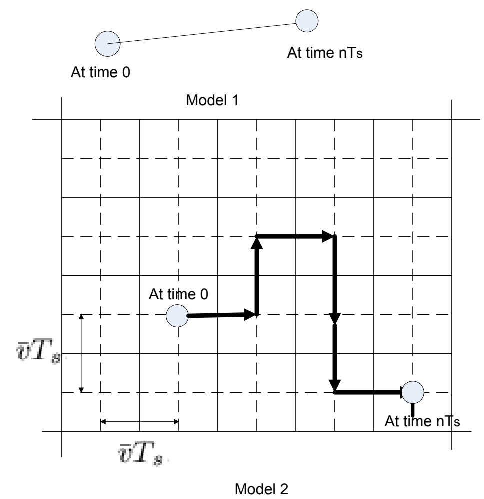

Fig. 1. Random mobility models of a mobile node

B. Detection model

We assume that each node has identical effective sensing range r with the sensing area of πr^2. Although we assume homogeneous sensor nodes for simplicity, the results can easily be extended for heterogeneous sensor nodes having different sensing ranges.

We assume a binary detection model in which the point P_0 is considered to be detected with probability 1 by the sensor s_k at time $t = nT_s$ if it lies in sensor-coverage area $C_k(nT_s)$ [11], where $C_k(nT_s)$ is the coverage area of node s_k at time nT_s for $n = 0, 1, 2, \cdots$. Formally, we can express the probability that the node s_k detects the target at time interval $[0, nT_s)$ as:

$$P_{d_k}(nT_s) = \begin{cases} 1 & \text{if} \quad P_0 \in C_k(nT_s) \\ 0 & \text{if} \quad \text{otherwise} \end{cases}$$

Note that for a static node, the coverage area $C_k(nT_s)$ is a constant over time. That is, if the target is not detected by a static node initially, it is not going to be detected forever. However, with a mobile node, since the coverage is varied over the time, there is a probability for the target to be detected as time goes.

C. Preliminaries

1) Boolean model: Let $\mathcal{P} \equiv \{\alpha_i, i \geq 1\}$ in $\mathbb{R}^k$ is a point process and $\{S_i, i \geq 1\}$ be a sequence of independently and identically distributed random sets, independent of $\mathcal{P}$. The collection of sets $\mathcal{C} = \{\alpha_i + S_i, i \geq 1\}$ is called a coverage process [14]. When $\mathcal{C}$ is driven by a stationary Poisson point process (i.e. $\mathcal{P}$ is a stationary Poisson point process), the coverage process $\mathcal{C}$ is called a Boolean model [14]. Since we assume that static node locations and initial mobile node locations are independently and identically distributed, the sensor locations can be modeled as a two-dimensional Poisson point process with intensity λ, when the total number of nodes and the sensing region are large.

2) Notation: We use $\mathcal{A}(S)$ and $\mathcal{P}(S)$ to denote the area and perimeter of the set S. Denote by $P + S$ the set centered at P with a shape of S.

IV. Stationary Target Detection Performance

In the following, we consider two modes of detection: Single-sesing detection and k-sensing detection [1]. In Single-sensing detection, the target is considered as detected if it is captured by at least one sensor. In k-sensing detection model, the target is considered as detected if it is detected by at least k sensors where k is a design parameter [1].

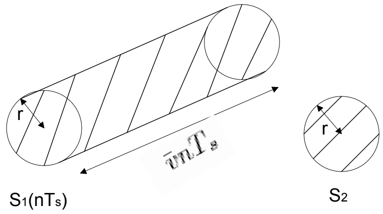

Fig. 2. Realization of random shapes at time nT_s

A. With random node mobility model 1

In this section, we analyze the detection performance with the random node mobility model 1, where the mobile nodes move in a straight line after selecting the direction independently and uniformly from $[0, 2\pi)$. Note that, with the assumption of large network sizes and the speed of a mobile node is small (e.g. for example, Robomote [15] mobile nodes have speed of $0.5 \sim 2m/s$), the average time a mobile node takes to leave the sensing region can be considered to be large. Our analysis is mainly focused on the region before the nodes leave the sensing region. The node locations at time nT_s can now be modeled as a Poisson point process with intensity λ [16] and the corresponding coverage area $S(nT_s)$ is distributed as

$$S(nT_s) = \begin{cases} S_1(nT_s) & with\ prob\ \lambda_m \\ S_2 & with\ prob\ 1-\lambda_m \end{cases},$$

where $S_1(nT_s)$ and S_2 are as shown in Fig. 2. The coverage area of k-th static sensor at time nT_s is given by,

$$C_k^s(nT_s) = C_k^s = \mathcal{A}(S_2) = \pi r^2,$$

and the coverage area of the k-th mobile node at time $t = nT_s$ is given by (corresponding to shape $S_1(nT_s)$),

$$C_k^m(nT_s) = \mathcal{A}(S_1(nT_s)) = \pi r^2 + 2rnT_s\bar{v}.$$

Thus the sensor network at time nT_s can be considered as a Boolean model. Then the probability that the target is detected is given by the following theorem.

Theorem 1: (*Detection probability*) The probabilities of detection with single-sensing and the k-sensing models ($k \geq 1$) at time $t = nT_s$ are given by,

$$P_D^1(nT_s) = 1 - e^{-\lambda(\pi r^2 + 2\lambda_m rn\bar{v}T_s)} \tag{1}$$

and

$$P_D^k(nT_s) = 1 - \sum_{j=0}^{k-1} \frac{(\lambda(\pi r^2 + 2\lambda_m rn\bar{v}T_s))^j e^{-\lambda(\pi r^2+2\lambda_m rn\bar{v}T_s)}}{j!}$$

respectively.

Proof: In single sensing detection, the target is considered as detected, if at least one sensor captures it. If $\mathcal{C} \equiv \{\alpha_i + S_i, i \geq 1\}$ is a Boolean model with shapes S_i are distributed as S, the number of sets (shapes) that intersects an arbitrary point (or the number of sets that covers an arbitrary point) in the Boolean model has a Poisson distribution with mean $\lambda E\{\mathcal{A}(S)\}$ [14]. At time $t = nT_s$, the hybrid sensor network consists of N_m number of mobile sensors having coverage areas of $\bar{C}^m(nT_s) = \pi r^2 + 2rnT_s\bar{v}$ and N_s number of static nodes having coverage areas of $C^s = \pi r^2$. Denote $P_{P_0}(m, nT_s)$ to be the probability that m number of sensors cover the point P_0 at time $t = nT_s$, which is given by [14]

$$P_{P_0}(m, nT_s) = \frac{\left(\lambda\bar{C}(nT_s)\right)^m e^{-\lambda\bar{C}(nT_s)}}{m!},$$

where $\bar{C}(nT_s) = (\lambda_m\bar{C}^m(nT_s) + (1-\lambda_m)C^s)$ is the average coverage area of the network at time nT_s. Then the probability that no sensor covers the point P_0, $P_{P_0}(0, nT_s)$, at time nT_s is given by, $P_{P_0}(0, nT_s) = e^{-\lambda\bar{C}(nT_s)}$. The probability of the single-sensing detection is thus given by,

$$\begin{aligned} P_D^1(nT_s) &= 1 - P_{P_0}(0, nT_s) = 1 - e^{-\lambda\bar{C}(nT_s)} \\ &= 1 - e^{-\lambda(\pi r^2 + 2\lambda_m rn\bar{v}T_s)}. \end{aligned}$$

In k-sensing detection, the target is considered to be detected if at least k sensors detect it. Probability that the point P_0 is covered by at least k sensors at time nT_s is given by,

$$\begin{aligned} P_D^k(nT_s) &= 1 - Pr(P_0 \text{ is covered by } k-1 \textbf{ or } \text{less sensors}) \\ &= 1 - \sum_{j=0}^{k-1} P_{P_0}(j, nT_s) \\ &= 1 - \sum_{j=0}^{k-1} \frac{(\lambda(\pi r^2 + 2\lambda_m rn\bar{v}T_s))^j e^{-\lambda(\pi r^2+2\lambda_m rn\bar{v}T_s)}}{j!}. \end{aligned}$$

■

Since allowing more nodes to be mobile is not desirable in many applications due to energy constraints, it is required to determine the minimum fraction of mobile nodes to be deployed in order to achieve the desired performance during a given time interval. The following theorem states the minimum fraction of mobile nodes required to achieve a desired probability level within a desired time interval for single sensing detection.

Theorem 2: (*Minimum mobile node density required with single sensing detection*) Let η_D be the desired detection probability to be achieved by the hybrid sensor network at time t_D. The minimum fraction of mobile nodes to be used to achieve η_D at time t_D with single-sensing detection model is given by,

$$\lambda_m^{min} = \begin{cases} \frac{-\log(1-\eta_D)-\lambda\pi r^2}{2\lfloor\frac{t_D}{T_s}\rfloor\lambda r\bar{v}T_s}, & \text{if } \eta_s \leq \eta_D \leq \eta_t \\ \text{Infeasible}, & \text{Otherwise}, \end{cases} \tag{2}$$

where $\eta_s = 1 - e^{-\lambda\pi r^2}$ and $\eta_t = 1 - e^{-\lambda[\pi r^2 + 2\lfloor\frac{t_D}{T_s}\rfloor r\bar{v}T_s]}$.

Proof: If the tolerable detection delay is t_D, and the desired detection probability is η_D, the minimum λ_m is characterized by,

$$\begin{aligned} &\min\ \lambda_m \\ &\text{such that } P_D^1\left(\left\lfloor\frac{t_D}{T_s}\right\rfloor T_s\right) \geq \eta_D \end{aligned},$$

where $P_D^1\left(\lfloor\frac{t_D}{T_s}\rfloor T_s\right)$ is given by (1). This leads to

$$\lambda_m \geq \frac{-\log(1-\eta_D) - \lambda\pi r^2}{2\lfloor\frac{t_D}{T_s}\rfloor\lambda r\bar{v}T_s}.$$

Note that (2) holds for a desired delay constraint, only if the desired detection probability η_D satisfies the condition $\eta_s \leq \eta_D \leq \eta_t$ where

$$\eta_s = 1 - e^{-\lambda\pi r^2}, \tag{3}$$

and

$$\eta_t = 1 - e^{-\lambda[\pi r^2 + 2\lfloor \frac{t_D}{T_s} \rfloor r\bar{v}T_s]}, \quad (4)$$

are the detection probabilities achieved by the network if all nodes are stationary ($\lambda_m = 0$), and if all nodes are allowed to move ($\lambda_m = 1$), respectively. ■

In the case of k-sensing detection, the minimum fraction of mobile nodes can be found by finding the minimum λ_m which satisfies the following inequality:

$$1 - \sum_{j=0}^{k-1} \frac{(\lambda(\pi r^2 + 2\lambda_m r\lfloor \frac{t_D}{T_s} \rfloor \bar{v}T_s))^j e^{-\lambda(\pi r^2 + 2\lambda_m r\lfloor \frac{t_D}{T_s} \rfloor \bar{v}T_s)}}{j!} \geq \eta_D,$$

However, if the desired delay constraint is such that $\lfloor \frac{t_D}{T_s} \rfloor \leq \frac{\pi r}{2\bar{v}T_s}$, the minimum fraction of mobile nodes can be found by finding the minimum λ_m which satisfies the following inequality:

$$\lambda_m - \frac{\log(f_1(k-1) + \lambda_m f_2(k-1))}{2\lambda r\lfloor \frac{t_D}{T_s} \rfloor \bar{v}T_s} \geq \frac{-\log(1-\eta_D) - \lambda\pi r^2}{2\lfloor \frac{t_D}{T_s} \rfloor \lambda r\bar{v}T_s}$$

where $f_1(k-1) = \sum_{j=0}^{k-1} \frac{(\lambda\pi r^2)^j}{j!}$ and $f_2(k-1) = \frac{2r\lfloor \frac{t_D}{T_s} \rfloor \bar{v}T_s}{\pi r^2} \sum_{j=1}^{k-1} \frac{(\lambda\pi r^2)^j}{(j-1)!}$.

B. With random node mobility model 2 (random walk)

Now we consider that the mobile nodes follow 2-D random walk mobility model at each time step nT_s as shown in Fig. 1. In this paper we consider only the case $r \leq \mu$, since if the step size is selected such that $\mu \ll r$, there are large overlaps in the sensing areas at consecutive steps [3]. Thus it is more desirable to select step size of the random walk such that $\mu \geq r$, which results in a larger coverage area at each step of the random walk. Since each mobile node performs independent and identical random walks at each time step, and the sensing range of each mobile node is identical, it can be seen that, $\{C_k^m(nT_s)\}_{k\in\mathcal{V}_m}$ are a set of independently and identically distributed random sets where $C_k^m(nT_s)$ is the area covered by the k-th mobile node by time nT_s. Denote $\bar{C}_k^m(nT_s) = \bar{C}^m(nT_s)$ to be the average coverage area of the k-th mobile node at time nT_s.

Let us assume that the sensing region can be viewed as a virtual square lattice having a total of $\approx \frac{b^2}{\mu^2}$ square sites where $\mu = \bar{v}T_s$ is the lattice side length. The k-th mobile node is assumed to be at the center of a site. If the mobile node starts to move at time $t = 0$, the expected number of distinct sites visited by time nT_s, $\mathbb{E}\{G(nT_s)\}$ can be approximated by [3], [17],

$$\mathbb{E}\{G(nT_s)\} \approx \frac{b^2}{\mu^2}\left(1 - \left(\frac{cb^2}{\mu^2}\right)^{-\frac{\pi n T_s}{\frac{b^2}{\mu^2}\log^2\left(\frac{cb^2}{\mu^2}\right)}}\right),$$

where $c = 1.8456...$. The average area covered by a mobile node at time nT_s, $\bar{C}^m(nT_s)$ is then given by the following theorem.

Theorem 3: (*Minimum average coverage area of a mobile node*) Assuming that $\mu \geq r$, the minimum average area covered by any single mobile node at time nT_s is given by,

$$\begin{aligned}\bar{C}^m_{min}(nT_s) &= \pi r^2 + (\mathbb{E}\{G(nT_s)\} - 1)^+ 2r\mu \\ &- (\mathbb{E}\{G(nT_s)\} - 2)^+(1 - \frac{\pi}{4})r^2, \quad (5)\end{aligned}$$

where $(x)^+$ equals to x if $x > 0$, and equals to zero otherwise.

Proof:

Assuming $\mu \geq r$, when there is $\mathbb{E}\{G(nT_s)\}$ number of distinct sites visited at time nT_s, there should be at least $\mathbb{E}\{G(nT_s)\} - 1$ number of steps to ensure that each point is connected to at least one lattice point (see Fig. 3). Then the minimum coverage area results if these lattice points are located such that each transition is orthogonal to the previous transition (That is, then the maximum amount of overlapping will occur with the minimum number of transitions). Figure 3 shows the realization of random walk when 4 distinct sites are visited with minimum number of (3) transitions. Fig. 3(a) is corresponding to $r \leq \frac{\mu}{2}$, where there is no overlapping of the sensing range while Fig. 3(b) corresponds to $\frac{\mu}{2} \leq r < \mu$ where there is overlapping of sensing range, between two consecutive steps. Based on geometric simplifications, in both cases as shown in Fig. 3, the minimum coverage area can be shown as,

$$\begin{aligned}\bar{C}^m_{min}(nT_s) &= \pi r^2 + (\mathbb{E}\{G(nT_s)\} - 1)^+ 2r\bar{v}T_s \\ &- (\mathbb{E}\{G(nT_s)\} - 2)^+(1 - \frac{\pi}{4})r^2,\end{aligned}$$

which completes the proof. ■

Then lower bounds for the detection probability in single-sensor and k-sensor detections can be shown as,

$$P_D^1(nT_s) \geq 1 - e^{-\lambda\bar{C}_{min}(nT_s)}, \quad (6)$$

and

$$P_D^k(nT_s) \geq 1 - \sum_{j=0}^{k-1} \frac{(\lambda\bar{C}_{min}(nT_s))^j e^{-\lambda\bar{C}_{min}(nT_s)}}{j!},$$

respectively, with $\bar{C}_{min}(nT_s) = \lambda_m\bar{C}^m_{min}(nT_s) + (1-\lambda_m)\pi r^2$ where $\bar{C}^m_{min}(nT_s)$ is given by (5).

Let η_D be the desired detection probability lower bound to be achieved by the hybrid sensor network at time t_D. The minimum fraction of mobile nodes λ_m^{min} that should be used in order to achieve this probability bound, within the desired time is stated in the following theorem:

Theorem 4: (*Minimum fraction of mobile nodes required to achieve a desired probability at a given time*) With single-sensing detection, if the desired detection probability lower bound, η_D, is to be achieved within a time interval t_D, the minimum fraction of mobile nodes that should be deployed in the hybrid network with single-sensing detection is given by

$$\lambda_m^{min} = \frac{-\log(1-\eta_D) - \lambda\pi r^2}{\lambda\left(\bar{G}_1(\lfloor\frac{t_D}{T_s}\rfloor T_s)2r\bar{v}T_s - \bar{G}_2(\lfloor\frac{t_D}{T_s}\rfloor T_s)(1-\frac{\pi}{4})r^2\right)}.$$

for $\mu \geq r$ where $\bar{G}_1(\lfloor\frac{t_D}{T_s}\rfloor T_s) = (\mathbb{E}\{G(\lfloor\frac{t_D}{T_s}\rfloor T_s)\} - 1)$ and $\bar{G}_2(\lfloor\frac{t_D}{T_s}\rfloor T_s) = (\mathbb{E}\{G(\lfloor\frac{t_D}{T_s}\rfloor T_s)\} - 2)$.

Proof: The proof follows directly from (6) and (5). ■

V. Simulation Results

A. With node mobility model 1

We verify the analytical results obtained in this paper via extensive Monte-Carlo simulations. The dimension of the sensing area is assumed to be $b = 1000m$, such that area is $1000 \times 1000m^2$. Mobile node speed is set to $\bar{v} = 1m/s$. Initially a total of $N = 500$ sensor nodes are deployed independently and uniformly in the sensing field. A fraction of 500 total nodes, is directed to move according to the random mobility model 1 as described in subsection III-A. Note that with these assumed parameters, it can be shown that the

(a). $r < \frac{\mu}{2}$ (b). $\frac{\mu}{2} \leq r < \mu$

Fig. 3. Minimum possible coverage area after completing 4 distinct steps

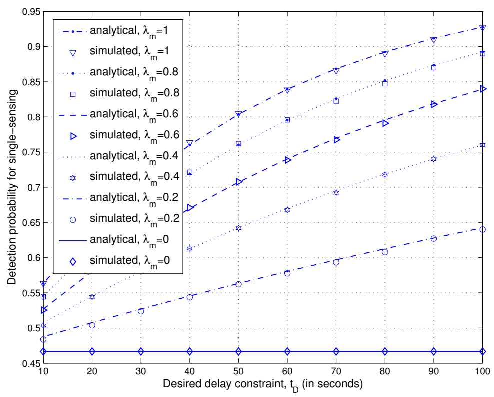

Fig. 4. Detection probability with single-sensing detection Vs desired delay constraint with mobility model 1: $r = 20m$

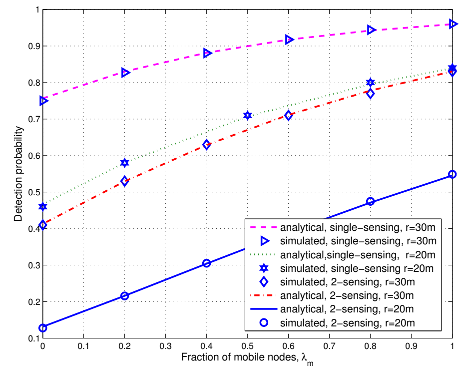

Fig. 5. Detection probability Vs fraction of mobile nodes in the network for single-sensing and 2-sensing detection models for mobility model 1; Desired detection delay is $t_D = 60s$.

average time a mobile node takes to leave the sensing region with the mobility model 1 is, $473.31655s$.

Figure 4 shows the time varying detection probability of the hybrid sensor network for single-sensing detection when the fraction of mobile nodes deployed is varied for a given sensing range for each node. In Fig. 4, we assume that $r = 20m$. From Fig. 4, we can see the derived analytical results almost exactly match with the simulation results. In Fig. 4, the results are shown for the region before nodes leave the sensing region. Although figures are not included it can be shown that (details are given in [18]), as the time increases, the detection probability saturates at a constant value. This phenomenon essentially reflects the detection probability corresponding to the maximum area that can be covered with the given fraction of mobile nodes before they leave the sensing region. It is also seen from Fig. 4 that by adding a small fraction of mobile nodes will boost the detection performance significantly compared to the stationary configuration, and the rate of performance improvement eventually decreases as λ_m increases. Also when the desired delay constraint is relatively large, a higher detection probability can be achieved with a relatively small fraction of mobile nodes, since then the mobile nodes have covered, on average a larger area of the sensing field.

Figure 5 shows the detection probabilities for single-sensing and 2-sensing detection models of the hybrid sensor network when the fraction of mobile nodes is increasing, for a given desired delay constraint. In Fig. 5 we let the delay constraint $t_D = 60s$ and plots are corresponding to varying sensing ranges (for $r = 20m$ and $r = 30m$). From Fig 5, the trade-off between sensing range of each node and the fraction of mobile nodes needed to achieve a desired probability at a desired delay constraint is shown. It can also be seen that the detection probability is nearly-linearly increasing, when the fraction of mobile nodes is increasing, for a given sensing range around the considered delay constraint (i.e. around relatively lower delay constraints).

In Fig. 6, the minimum fraction of mobile nodes required to achieve a desired performance level within a desired delay constraint is shown for $r = 20m$ and $r = 30m$ with single sensing detection. It is seen that when the desired delay constraint is small, the minimum fraction of mobile nodes is increasing to achieve a desired performance level. Moreover, the impact of the mobile node density on the detection performance is more significant when the sensing range of the nodes is small, which is the most practical scenario in many sensor networks. In other words, it can be seen from Fig. 6 that when the sensing range is increasing, the variation of the required fractions of mobile nodes to achieve different detection thresholds, is less compared to that with lower sensing ranges.

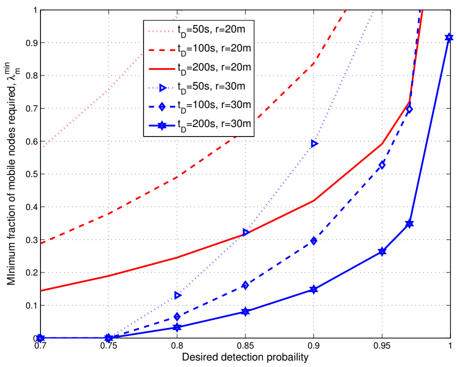

Fig. 6. Minimum fraction of mobile nodes required to achieve a desired performance level within a desired delay constraint for mobility model 1

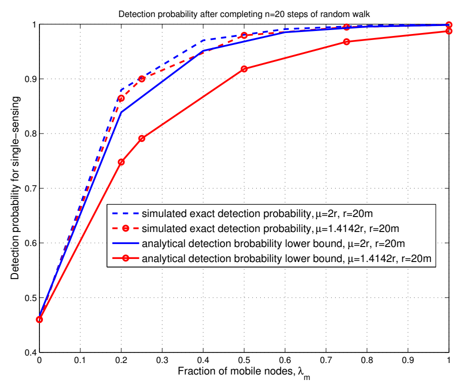

Fig. 7. Detection probability lower bound with single-sensing detection Vs fraction of mobile nodes in the network with random walk mobility model after completing $n = 20$ steps: for $\mu = \sqrt{2}r$ and $\mu = 2r$: $r = 20m$

B. With node mobility model 2

To see the performance of the derived detection probability lower bound, we perform Monte-Carlo simulations to obtain the exact detection probability with random walk mobility model. Figure 7 shows the analytical detection probability lower bound and the exact detection probability vs the fraction of mobile nodes, with random walk mobility model after completing $n = 20$ steps. In Fig. 7, we let the step sizes of the random walk to be $\mu = \sqrt{2}r$ and $\mu = 2r$ where r is set to $r = 20m$. From Fig. 7, it can be seen that the derived lower bound is a good match for the exact detection probability. Moreover, when the step size of the random walk is selected relatively larger compared to the sensing radius of the node, it can be seen that the derived lower bound becomes a very good approximation for the exact detection probability. For a given sensing range, selecting a larger step size compared to the sensing range is more desirable in performing 2-D random walk, since then the overlapping of sensing coverage at consecutive steps is reduced.

VI. Conclusion

In this paper, we considered the problem of target detection in a hybrid sensor network consisting of both static and mobile nodes and derived analytical expressions that are important in designing such sensor networks. Static node locations and initial locations of mobile nodes are assumed to be independently and identically distributed in the sensing region. Nodes are assumed to move randomly and independently searching for targets. Detection probabilities for single-sensing and k-sensing detection models were derived for the hybrid sensor network. Since deploying mobile nodes is not as cost effective as deploying static nodes, we characterized the minimum fraction of mobile nodes to be combined with static nodes in order to meet the desired system performance within a desired delay constraint after initial deployment. The analytical results derived in this paper help to select design parameters in hybrid sensor networks for on-demand application requirements.

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