Analytic Modeling of Detection Latency in Mobile Sensor Networks

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ABSTRACT

An envisioned usage of sensor networks is in surveillance systems for detecting a target or monitoring a physical phenomenon in a region. Traditionally, stationary sensor networks are deployed to carry out the sensing operations. In many applications, if the monitored region is relatively large compared to the sensing range of a node, a large number of nodes are required in the region to achieve high coverage. Using mobile nodes in such situations can be an attractive alternative. Mobility of sensor nodes has been studied in sensor networks for many purposes such as power saving, data collection, and packet delivery. However, nearly all research literature for the target detection problem has focused on stationary sensor networks. This paper investigates the problem of detecting the presence/absence of a target using mobile sensor networks. It presents an analytic method to evaluate the detection latency based on a collaborative sensing approach using nodes with uncoordinated mobility. We verify the analytic model through simulations. The analytic method provides a simple way of analyzing the tradeoff between number of nodes and detection latency in a mobile sensor network. The analysis is also used to compare the performance of mobile and stationary sensor networks with respect to these measures. Results show that if the target is present at the worst possible location in a given deployment, then detection latency of mobile sensor networks is considerably less as compared to that of stationary networks with the same number of nodes.

Categories and Subject Descriptors

C.4 [**Performance of Systems**]: Modeling techniques, Performance attributes; C.3 [**SPECIAL-PURPOSE AND APPLICATION-BASED SYSTEMS**]: Real-time and embedded systems

General Terms

Theory, Performance, Algorithms

Keywords

Mobile sensor networks, Collaborative detection, Detection latency, Analytic model

1. INTRODUCTION

Technological advances in integrated circuit design, communications, and networking have enabled the production of sensor nodes capable of measuring the environment, processing information, and answering queries. Equipped with wireless communication capabilities, the nodes can form a network to detect intruders or observe environment in the region of interest. Such networks not only provide a convenient bridge between the computational space and the physical environment, but will also significantly impact the way we observe the world in the future.

For many envisioned applications, a stationary network is usually adequate to meet the application requirements. As a result, most research in literature have focused on stationary sensor networks. Unlike these prior investigations, the focus of this paper will be on sensor networks in which the nodes are *mobile*. We contend that there are many applications for which sensor networks with mobile devices are better suited than a stationary network.

For instance, consider the problem of detecting a biochemical attack in a battlefield environment. The conventional stationary sensor network approach is to deploy a large number of devices with appropriate sensing capabilities in the battlefield. The nodes in the network sample their environment, exchange the sensed information, and fuse the information gathered to arrive at a consensus decision about the biochemical attack. If the battlefield area is large relative to either the sensing or the communication range of each device, the number of devices required to cover the entire region is also typically large. For example, if the area of battlefield region is l^2, r is the communication range of each device, and devices are uniformly and randomly deployed in the field, then $O(\frac{l^2 \log l}{r^2})$ devices will be needed to ensure network connectivity with sufficiently high probability [1]. Similar density constraints have also been derived based on sensing range for stationary networks.

An alternative, and possibly more attractive, approach is to deploy a network with mobile devices for dealing with the above problem. For instance, the troops and/or vehicles in the battlefield can carry the biochemical sensors while doing their normal daily activities. Since the troops and the vehicles are likely to be moving as part of their daily activities, the associated sensing devices are also on the move. These *mobile* sensing devices can sample the environment at potentially several different locations, exchange the information with other devices and/or fusion center, and collaboratively make a decision for the presence of the biochemical attack. Since the mobility of the nodes in this approach is not based on the need for sensing, we refer to it as *uncoordinated mobility* (UM). The focus of this paper is on sensor networks with such UM. This is in contrast to research on sensor networks with planned or adaptive mobility in which the nodes move with the specific objective of improving the performance of sensing, communicating, and/or collaborative decision-making [2–14]. Although sensor networks with planned or adaptive mobility are likely to have better performance than networks with uncoordinated mobility, this paper shows that one can exploit intrinsic mobility in the application environment to seamlessly carry out effective sensing and collaborative decision-making, especially in the context of target detection.

Specifically, this paper develops an analytic method to compute the latency of detecting a target in a sensor network with UM. Detection latency is a critical factor for applications designed to detect hostile targets or dangerous phenomena. For instance, the target can be a wild fire occurring in a forest, an enemy vehicle hiding in the battlefield to spy on the activities of the troops, and/or a radiological dispersion device (RDD) which can emit non-fissile but highly radioactive particles in the monitored region. It is important to assure that the deployed nodes can detect such targets within a certain amount of time.

The approach analyzed in this paper assumes that the sensor nodes periodically report their measurements from possibly different locations to a control center. The control center fuses the measurements from all the nodes (made at approximately the same time instant) to reach a consensus decision on the presence/absence of the target. The fusion scheme is such that the probability of false alarm is below a specified threshold. *Detection latency* at a given instant is the difference between the time at which the target is first detected and its time of arrival. Since the time of first detection is a random variable, we characterize the effectiveness of the approach using the following measure. We consider detection latency such that the probability of detection is above a given threshold subject to the specified false alarm rate.

The main contributions of the paper are three-fold. The paper first presents a collaborative sensing architecture with UM nodes. It then proposes an analytic method to evaluate the detection latency. The analytic method is verified by simulations with matching results. Finally, it evaluates the tradeoff between number of nodes and detection latency for both mobile and stationary sensor networks. The tradeoff analysis provides a quantitative way of comparing mobile and stationary sensor networks with respect to their effectiveness in detecting idling targets. An interesting observation from this comparison is that if the target can be located at the worst possible location for a given deployment, then the mobile sensor networks outperform stationary networks in terms of detection latency for the same number of nodes. This is counter-intuitive to the conventional wisdom that mobile networks tend to have larger latency than stationary networks.

The rest of the paper is organized as follows. In Section 2, the analytic model for evaluating detection latency in mobile sensor networks with UM nodes is presented. Section 3 verifies the analytic results by simulation. In Section 4, the comparison of mobile and stationary sensor networks is presented. The most related work is reviewed in Section 5. The paper concludes in Section 6.

2. MODELING DETECTION LATENCY

2.1 Sensing Architecture

Assume that n sensing nodes are deployed in a square region. The nodes carry a sensor to detect a signal emitted by a certain target. The nodes are tasked to sense for this signal and to reach a consensus on whether or not the target is present in the region. To reach this consensus, each node measures the energy of the target signal and periodically reports its energy measurement to a fusion center.

The movement of a node is not planned or adapted with an objective of detecting the target. Furthermore, the movement of each node is modeled as a random walk such that in each measurement period the node moves to a new location that is uniformly distributed within a radius r of its current location.

For making the consensus decision, the fusion center compares the average of the detected energy measurements of all the nodes to a threshold η_n. If the average is greater than η_n, the fusion center decides that a target is present. Otherwise, it decides that there is no target. Due to noise in each node's energy measurements, the consensus decision may be erroneous. In particular, the consensus decision may be a *false alarm*, i.e., although there is actually no target in the region, the consensus decides that a target is present. The parameter η_n is chosen such that a false alarm probability is below a specified threshold.

For simplicity of presentation, the paper assumes that each node can directly communicate with the fusion center in each measurement period. The focus of this paper is on evaluating the detection latency due to sampling, collaboration, and noise. If direct communication to the fusion center is not always possible, additional latencies may occur due to multi-hop wireless communication. This additional latency is not modeled in this paper.

2.2 Energy Model

Let each node acquire one energy measurement per period of time instant, and let $\{s_i(t),\ i = 1, ..., n\}$ be the node locations at time t. Based on a general radio propagation model [15], the signal energy of a target is assumed to decay as a power of the distance from the target. Thus, if a target is present at location u emitting a signal of energy K, the target energy detected by a node at position $s_i(t)$ is given by

$$E_i(t) = \begin{cases} \frac{K}{|u - s_i(t)|^\beta} & \text{if } |u - s_i(t)| > 1 \\ K & \text{otherwise,} \end{cases} \tag{1}$$

where β is the decay factor and $|u - s_i(t)|$ is the Euclidean distance between the target and the node. In normal environment, β is typically between 2 to 5 [16].

Energy detected by the nodes is usually corrupted by noise. Let N_i^2 denote the noise energy detected by node

i. The total energy detected by node i at time t is the sum of target energy and noise energy, i.e., $E_i(t) + N_i^2$.

2.3 Detection Probability

The fusion center compares the average of the energy readings to a threshold. Given there exists a target, the probability of detecting the target at time t can be expressed as

$$D(t) = P\left(\frac{1}{n}\sum_{k=1}^{n}(E_k(t) + N_k^2) > \eta_n\right), \quad (2)$$

where η_n is the energy threshold for n nodes.

False alarms may occur in the consensus decision due to the presence of noise. The sensor network may incorrectly decide that a target is present when there is actually no target in the region, i.e., $E_k(t) = 0$. Assume that the noise N_i is Additive White Gaussian Noise (AWGN) with mean zero and variance one and independent at each node. The noise energy can be modeled as N_i^2 which is a Chi-Square random variable with one degree of freedom. Then, the false alarm probability is given by

$$D_f = 1 - F_{\chi_n^2}(n \cdot \eta_n),$$

where $F_{\chi_n^2}(\cdot)$ is the cdf of Chi-Square with n degrees of freedom. Note that $\sum_{k=1}^{n} N_k^2$ is a Chi-Square random variable with n degrees of freedom. Therefore, given a tolerable false alarm probability D_f, one can determine the corresponding threshold η_n. In general, detection probability and false alarm probability are closely related. A higher detection probability always comes with a higher false alarm probability.

2.4 Detection Latency

Detection latency characterizes how soon the sensor network can detect the presence of a target after it arrives. It is important especially when the target is hostile or malicious. Let τ denote the random variable of the difference between the time of first detection and time of target arrival, and $P(\tau \leq t)$ denote the probability of detecting the target within time t. Detection latency is formally defined as follows.

Definition (*Detection Latency*): The detection latency of a sensor network is defined as a duration t such that $P(\tau \leq t)$ is above a given threshold P_{th}. ■

If each node can move far enough at each measurement period such that consecutive detection results are independent, then, from the fusion scheme, the probability distribution function of τ is

$$P(\tau \leq t) = \sum_{i=1}^{t}\left(\prod_{j=1}^{i-1}(1 - D(j))\right) D(i). \quad (3)$$

However, the above assumption may not be true for every application. Instead, in a sensor network with UM nodes, we can rely on a probabilistic model of node mobility to characterize the transitions of the average target energy and thereby calculate the detection latency. In fact, the transition of the target energy from time t to time $t+1$ also reflects the transition of node locations. If the node mobility is modeled as a random walk, then a Markov chain can be used to analytically evaluate the detection latency.

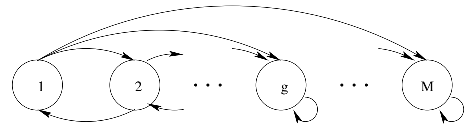

Figure 1: The Markov chain for target energy transition.

2.5 Energy Band Model

Assume that the target is present at position u in the region. Consider n UM nodes in an $\ell \times \ell$ region when a target is present at the center of the region. Let $\overline{E}(t)$ and $\overline{N^2}$ denote the average target energy and average noise energy detected by the nodes, i.e., $\overline{E}(t) = \frac{1}{n}\sum_{k=1}^{n} E_k(t)$ and $\overline{N^2} = \frac{1}{n}\sum_{k=1}^{n} N_k^2$. The transition of $\overline{E}(t)$ from time t to $t+1$ can be associated with a discrete time Markov chain with continuous state space. Note that $\overline{E}(t)$ falls in the band between K and K_{min}, where K_{min} is the minimum of the average target energy depending on the size of the region.

Instead of using a Markov chain with continuous state, the proposed method adopts an approximation that divides the energy band evenly into M states. The granularity of the states trades off accuracy with the computational load. The states are defined as follows.

- Let $I = (K - K_{min})/M$. For $1 \leq i \leq M$, state i represents the energy interval $(\lambda_{i-1}, \lambda_i]$, where $\lambda_{i-1} = K_{min} + (i-1) \times I$, and $\lambda_i = K_{min} + i \times I$.
- For each state, let $e_n^i = (\lambda_{i-1} + \lambda_i)/2$ be the approximated energy value in state i, and $e_n^1 < e_n^2 < ... < e_n^M$, where n denotes the number of nodes.

Let $(X_t)_{t \geq 1}$ be a discrete time Markov chain. The Markov chain is constructed as follows.

- Let state g be the first state that $e_n^g > \eta_n - 1$.
- For $i < g$,

$$P(X_{t+1} = j | X_t = i) \\ = P\left(\overline{E}(t+1) = e_n^j | \overline{E}(t) = e_n^i\right), \quad 1 \leq j \leq M.$$

- For $i \geq g$,

$$P(X_{t+1} = j | X_t = i) = \begin{cases} 1, & \text{if } i = j \\ 0, & \text{if } i \neq j \end{cases}$$

Figure 1 shows the structure of the Markov chain. Several issues must be clarified. First, if the average target energy is greater then $\eta_n - 1$, the model decides that a target is present. The Markov chain only characterizes the transition of the detected target energy. However, if noise is not considered, the estimated detection probability can be inaccurate. If the noise process at each node is AWGN with mean zero and variance one, then the average noise energy $\overline{N^2} = 1$. For simplicity of presentation, we use $\eta_n - \overline{N^2}$ as the detection threshold. We can also couple the noise energy in the Markov chain to make a better approximation.

Second, the states greater than g are made absorbing since the objective of the model is to determine whether the target has been detected rather than when it is detected. Once a state greater than g is reached, a detection event occurs, and the state should remain unchanged thereafter.

With this model, estimating the probability of detecting a target within duration t is equivalent to calculating the probability that X_t is greater than g at time t, i.e.,

$$P(\tau \leq t) = P(X_t \geq g). \quad (4)$$

It is easy to calculate Eq.(4) using the Markov chain. Let π_n^t be the probability distribution of the Markov chain at time t and T_n be the transition matrix for n nodes. The distribution of the Markov chain at time t is given by

$$\pi_n^t = \pi_n^{t-1} T_n.$$

Finally, the detection probability within time t is

$$P(\tau \leq t) = \sum_{i=g}^{M} \pi_n^t[i], \quad (5)$$

where $\pi_n^t[i]$ is the ith element in π_n^t. Further, the detection latency is the time t when $P(\tau \leq t) \geq P_{th}$. The distribution π_n^t can be calculated if the initial distribution π_n^0 and the transition matrix T_n are given. The values of π_n^0 and T_n can be obtained by analytic method or by simulations. The analytic method is discussed in the rest of this section.

2.6 Initial Distribution

To calculate π_n^0, we first observe the initial distribution π_1^0 for one node. In this case, we can convert the energy intervals to the corresponding rings centered at the target's location, where ring i is the area between two circles centered at the target with radius $\sqrt{K/\lambda_i}$ and $\sqrt{K/\lambda_{i-1}}$. If UM nodes are uniformly distributed in the region, for the single node case, the probability that the node is in energy interval i can be computed by the ratio of the area of the corresponding ring to the total area of the region. Specifically, assume that the target is in the center of the region. If A is the total area of the region and a_i is the area of the ring associated with the ith energy interval, the probability of the node in energy interval i is

$$\pi_1^0[i] = P(E_1(0) = e_1^i) = \frac{a_i}{A}. \quad (6)$$

Since a square region is considered, we choose $K_{min} = K/(\frac{\ell}{2})^2$, where ℓ is the width of the square region, and the outermost ring covers the corners of the region.

For n nodes, the initial distribution is

$$\pi_n^0[i] = P(X_0 = i) = P\left(\sum_{k=1}^{n} E_k(0) = ne_n^i\right). \quad (7)$$

Since the movement of the nodes are independent, Eq.(7) is the probability mass function of the sum of n independent random variables $E_1(0)$, which is equivalent to the convolution of the corresponding n probability mass functions [17]. Thus, the initial distribution for n nodes can be obtained by

$$\pi_n^0 = \underbrace{\pi_1^0 \otimes \pi_1^0 \otimes \cdots \otimes \pi_1^0}_{n \text{ times}} \quad (8)$$

Moreover, Eq.(8) can also be computed by taking the discrete-time Fourier transform (DFT) of π_1^0, raising it to the power of n in the frequency domain, and then taking the inverse discrete-time Fourier transform (IDFT) of the result.

Indeed, DFT assumes the input signals are periodic, but π_1^0 is non-periodic. Hence, π_1^0 must be zero padded before taking the DFT. If the number of the energy intervals for one node is m, the length of π_1^0 must be extended to $M = nm - n + 1$ with zero padded.

2.7 Transition Matrix

Similar to the initial distribution, the transition matrix for n nodes can also be calculated from one node estimation in a slightly different way. Let ψ_1^0 be a matrix of the joint probability of the current state and the next state for a single node at time zero, i.e.,

$$\psi_1^0[i,j] = P(E_1(1) = e_1^j, E_1(0) = e_1^i), \; \forall\, 1 \leq i, j \leq m,$$

where m is the number of states for the single node case. In the case of n nodes deployed, $\psi_n^0[i,j]$ can be expressed as

$$\psi_n^0[i,j] = P\left(\sum_{k=1}^{n} E_k(1) = ne_n^j, \sum_{k=1}^{n} E_k(0) = ne_n^i\right) \quad (9)$$

where $1 \leq i, j \leq M$ and $M = nm - n + 1$. The joint probability is formed by two dimensions and each dimension is the sum of n random variables. Analogously, Eq.(9) can be calculated using the two dimensional convolution of one node's joint probability as shown in the following proposition.

Proposition: Let ψ_2^0 be the matrix of the joint probability of the current state and the next state at time zero for two nodes as defined in Eq.(9). Then,

$$\psi_2^0 = \psi_1^0 \otimes_2 \psi_1^0,$$

where $\otimes_2$ denotes the two dimensional convolution.

Proof:

Let u and v be the energy values of any two energy intervals. For two nodes, ψ_2^0 can be expressed as follows.

$$\begin{aligned}
&P\left(E_1(t+1) + E_2(t+1) = u, E_1(t) + E_2(t) = v\right) \\
&= \sum_{i=1}^{m}\sum_{j=1}^{m} P\left(E_1(t+1) = e_1^i, E_2(t+1) = u - e_1^i,\right. \\
&\qquad\left. E_1(t) = e_1^j, E_2(t) = v - e_1^j\right) \\
&= \sum_{i=1}^{m}\sum_{j=1}^{m} P\left(E_1(t+1) = e_1^i, E_1(t) = e_1^j\right) \\
&\qquad \times P\left(E_2(t+1) = u - e_1^i, E_2(t) = v - e_1^j\right)
\end{aligned}$$

The last equality follows from the fact that each node moves independently. It is obvious that the last expression is a two dimensional convolution. ■

From the proposition, ψ_n^0 can be calculated by convolution of ψ_1^0,

$$\psi_n^0 = \underbrace{\psi_1^0 \otimes_2 \psi_1^0 \otimes_2 \cdots \otimes_2 \psi_1^0}_{n \text{ times}}. \quad (10)$$

Again, the two dimensional DFT and IDFT can be exploited to calculate ψ_n^0.

Let us consider the transition probability from state i to j for n nodes. If state g is the first state that $e_n^g > \eta_n$, the transition matrix can be described as follows.

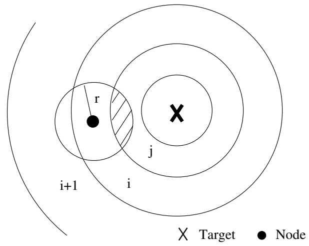

Figure 2: $P(E_1(t+1) = e_1^j | E_1(t) = e_1^i)$

- For $1 \le i < g$:

$$T_n[i,j] = P\left(\sum_{k=1}^{n} E_k(1) = ne_n^j \,\middle|\, \sum_{k=1}^{n} E_k(0) = ne_n^i\right) \tag{11}$$

$$= \frac{P\left(\sum_{k=1}^{n} E_k(1) = ne_n^j, \sum_{k=1}^{n} E_k(0) = ne_n^i\right)}{P\left(\sum_{k=1}^{n} E_k(0) = ne_n^i\right)} \tag{12}$$

$$= \frac{\psi_n^0[i,j]}{\pi_n^0[i]}, \qquad \forall\, 1 \le j \le M. \tag{13}$$

- For $g \le i \le M$:

$$T_n[i,j] = \begin{cases} 1, & \text{if } i = j \\ 0, & \text{if } i \ne j \end{cases}, \quad \forall\, 1 \le j \le M. \tag{14}$$

The denominator of Eq.(13) is the initial distribution which is described in the previous sub-section and the numerator can be obtained from Eq.(10). Thus, if ψ_1^0 is given, the transition matrix T_n can be calculated as in Eq.(13) and (14).

To estimate ψ_1^0, we first estimate the conditional probability $P\left(E_1(1) = e_1^j | E_1(0) = e_1^i\right)$ as shown in Figure 2. The circles centered at the target are the geographical boundaries of the energy intervals. Since a node is equally likely to move to any location within a radius r of its current location, if the node is in the median of ring i, then

$$P\left(E_1(1) = e_1^j | E_1(0) = e_1^i\right) = \frac{b_j}{B}, \tag{15}$$

where b_j is the area of the shadowed region in Figure 2 and $B = \pi r^2$ is the area that the node can move in one time instant. Since the node is randomly placed in the area, without loss of generality, we assume that the node departs from the median of the ring. By Eq.(6) and Eq.(15), ψ_1^0 is given by

$$\begin{aligned} \psi_1^0[i,j] &= P\left(E_1(1) = e_1^j, E_1(0) = e_1^i\right) \\ &= P\left(E_1(1) = e_1^j | E_1(0) = e_1^i\right) \times P(E_1(0) = e_1^i) \\ &= \frac{bi}{B} \times \frac{a_i}{A}. \end{aligned}$$

The transition matrix is thus obtained. The complete procedure for evaluating the detection latency in mobile sensor networks with UM nodes is shown in Figure 3.

Procedure Latency(n)
-Evaluate the one-node initial distribution π_1^0 and the joint probability ψ_1^0 with m states.
-Extend π_1^0 to length $M = nm - n + 1$ with zero padded.
-Extend ψ_1^0 to size $M \times M$ with zero padded.

$\Pi_1^0 = \text{DFT}(\pi_1^0)$;
$\Pi_n^0[i] = \Pi_1^0[i]^n, \quad \forall\, 1 \le i \le M$;
$\pi_n^0 = \text{IDFT}(\Pi_n^0)$;

$\Psi_1^0 = \text{DFT2}(\psi_1^0)$;
$\Psi_n^0[i,j] = \Psi_1^0[i,j]^n, \quad \forall\, 1 \le i,j \le M$;
$\psi_n^0 = \text{IDFT2}(\Psi_n^0)$;

For $1 \le i < g$:
  $T_n[i,j] = \frac{\psi_n^0[i,j]}{\pi_n^0[i]}, \quad \forall\, 1 \le j \le M$;
end
For $g \le i \le M$:
  $T_n[i,j] = \begin{cases} 1, & \text{if } i = j \\ 0, & \text{if } i \ne j \end{cases}, \quad \forall\, 1 \le j \le M$;
end
$t = 0$;
Do
  $t = t + 1$;
  $\pi_n^t = \pi_n^{t-1} T_n$;
  $P(\tau \le t) = \sum_{i=g}^{M} \pi_n^t[i]$;
while($P(\tau \le t) < P_{th}$)
return(t);
End Procedure

Figure 3: The procedure for evaluating the detection latency.

3. SIMULATION

Simulations are conducted to verify the accuracy of the detection latency obtained with the analytic method for mobile sensor networks with UM nodes. In the simulations, UM nodes are deployed in a 40×40 square region. Assume that a target is present in the center of the region, and the energy emitted by the target is $K = 30$ with the decay factor $\beta = 2$. The mobile nodes are randomly placed at the start of the simulations. During each simulation time instant, the nodes execute three basic operations including taking measurements, collaboratively making a consensus decision on the presence/absence of the target, and moving to the next sensing locations. Noise is assumed to be AWGN with mean zero and variance one. A node can move to any place within a radius $r = 2$ from its current location in each time instant. The fusion threshold η_n is chosen such that the false alarm probability is 0.001 for the consensus decision. Note that η_n has to be adjusted with different number of nodes in order to compare the detection probability based on a fixed false alarm probability. The target is assumed to appear at time zero and each deployment is run until the target is detected or 500 time steps have elapsed. The simulation was repeated for 10,000 deployments. The probability of detecting the target within a latency t is computed as the ratio of the number of deployments which detect the target within time t over the total number of deployments.

The analytic results are calculated using the same parameters for the nodes, the target, and the region size. For the initial one node analysis, the energy band is divided into 80 states. The initial distribution π_1^0 and the joint prob-

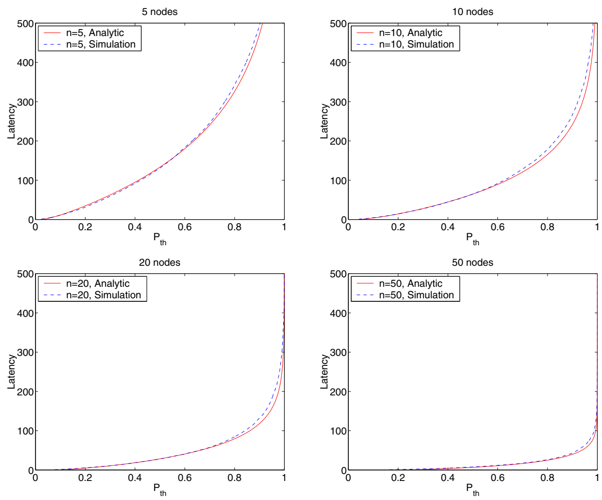

Figure 4: Detection latency at a 40 $\times$ 40 region.

ability ψ_1^0 for one node are first calculated. By DFT and IDFT, the initial distribution π_n^0 and the transition matrix T_n for n nodes can be calculated. The analytic and simulation results for 5, 10, 20, and 50 nodes are shown in Figure 4. Observe that, the detection latencies obtained by the analytic method match the simulation results very well for all the cases. This shows that our analytic model can accurately estimate the detection latency. The small error is caused by discretization of the energy band for the Markov chain.

4. ASSESSMENT

Given the proposed model, we are able to compare the detection latency of mobile sensor networks and stationary sensor networks. The parameters for the following analysis are the same as those used in the previous section except the target location. The nodes are still deployed in a 40 $\times$ 40 region. The target may be present on any grid point of the 10 $\times$ 10 region as shown in Figure 5. This setting is closer to practical situations where a smart target can choose a place to stay and carry out its mission. Sensors are also deployed in a region larger than the monitored region to better cover the boundary of the monitored region. Since the target can appear on any one of the grid points, we compare the detection latency at the *worst* possible location for the target in mobile and stationary networks. We refer to the worst location for the target as the *exposed location*.

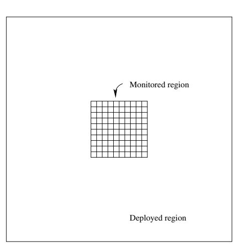

Figure 5: The region under monitoring.

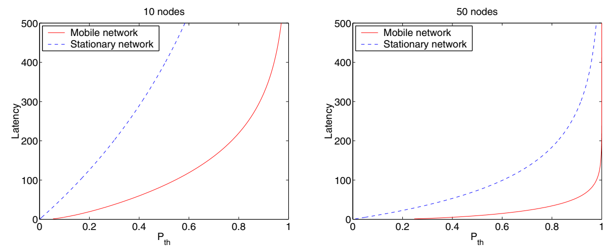

Figure 6: The worst-case detection latency.

To find the *worst-case detection latency*, the exposed location is first determined. Given a stationary sensor network, the probability of detecting a target on a specific grid point can be determined by Eq.(2). The exposed location is the grid point where the detection probability is minimal. Since the detected target energy readings are deterministic and noise process is independent at each node, consecutive detections are independent. By Eq.(3), the probability of detecting the target within time t is given by

$$P(\tau \leq t) = \sum_{i=1}^{t} (1 - \mathcal{P})^{i-1} \mathcal{P}, \tag{16}$$

where $\mathcal{P}$ is the minimal detection probability over all the grid points. Note that Eq.(16) is calculated for a specific stationary sensor deployment. For fair comparison, the average of Eq.(16) over 10,000 random deployments is taken for stationary sensor networks. The detection latency is the time that the average of the worst cases is above a threshold P_{th}.

For mobile sensor networks, since the target location can be at any of the grid points, the one-node initial probability π_1^0 and the joint probability ψ_1^0 are found for each target location via a one-step simulation. The one-step simulation randomly deploys a node in the region and simulates one move for the node. It collects the statistics of the target energy detected by the node before and after the move so that π_1^0 and ψ_1^0 can be determined. Then, using DFT and IDFT on the π_1^0 and ψ_1^0, the initial probability π_n^0 and the transition matrix T_n for n nodes can be calculated. The exposed location is chosen as the grid point where it takes the longest time to reach 80% detection probability if a target is present on the corresponding grid point. The detection latency is measured by the duration from the time of the target's arrival to the time when the detection probability is above the threshold P_{th}.

The results of the worst-case detection latency for 10 nodes and 50 nodes are shown in Figure 6. For mobile sensor networks, the exposed location is (15, 15), which is one of the corners of the monitored region. The detection probability on the corners of the monitored region is, on average, slightly lower than the center but the difference is small. From the figures, the worst-case detection latency of mobile sensor networks is shorter than the average worst-case detection latency of stationary sensor networks in both deployments of a small number of nodes (10) and a large number of nodes (50). The reason is that, in mobile sensor networks, nodes have the chance to move closer to the target no matter where the target is. In other words, there is less chance for the target to find a "hole" in the monitored region.

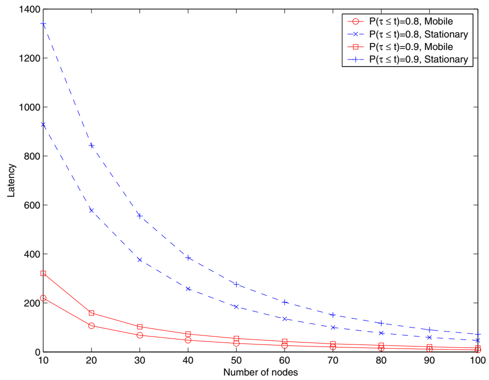

Figure 7: Detection time v.s. number of nodes at a 40× 40 region.

Figure 7 shows the number of nodes versus the worst-case detection latency for P_{th} equal to 80% and 90%. As shown in the figure, the more the nodes deployed, the shorter the worst-case detection latencies for both mobile and stationary sensor networks. On average, the worst-case detection latency is smaller for mobile sensor networks as compared to that for stationary networks with the same number of nodes. The difference between the two decreases as the number of nodes increases. If the number of nodes is large, then the worst-case detection latencies of stationary and mobile networks are comparable. This figure illustrates the advantage of using mobile sensor networks over stationary networks.

Another useful information in Figure 7 is a comparison of the cost of mobile and stationary sensor networks. For example, if the tolerable detection latency to reach 80% detection probability is 200 time units, then either 11 mobile nodes or 50 stationary nodes are required to be deployed. If the cost of a mobile node is less than 5 times of a stationary node, it is probably worth to deploy mobile nodes instead of stationary nodes. If the sensing nodes are carried by personnel and/or vehicles, then the cost difference between mobile and stationary nodes may not be considerable.

5. RELATED WORK

For surveillance purposes, coverage and exposure are two critical issues in stationary sensor networks [18, 19]. Mobility of nodes has been exploited to improve the coverage in sensor networks [20–22]. In [20], a potential field based approach is proposed to deploy the nodes. Forces due to the fields constructed among the nodes and obstacles repel the nodes to spread out in a given area. A similar virtual force algorithm is proposed in [21]. The virtual force between two nodes can be attractive or repulsive depending on the distance between the nodes. The algorithm computes the final locations for the nodes to increase the coverage iteratively and move the nodes from their initial random locations to the computed final locations in one step. Several algorithms for finding the desired locations to redeploy the nodes are proposed in [22]. The authors use Voronoi diagrams to identify the coverage holes in the network and move the nodes to improve the coverage. In these studies, although mobility is used to deploy nodes, the nodes are ultimately static in the network. In contrast, we focus on sensor networks in which nodes are moving persistently during the detection operations.

Coverage of mobile sensor networks with continuously moving nodes is studied in [23]. The authors investigate the area coverage at a given time instant as well as during a time interval. They also investigate the detection time of an intruder in the network. However, the sensing model of the work is fairly simple. A point is covered if it is within the sensing range of a node. Without considering noise and fusion, the result may deviate far from the reality.

A few recent studies have focused on the design of mobile sensing platforms [6, 7] and their applications [8–11]. For instance, in [10], mobile sensors are used to collaboratively perform surveillance of a region. Much experience can also be borrowed from robotics research where mobile robots plan their routes to achieve various objectives. Specifically, the pursuit-evasion games of robots bear a similar form of a mobile sensing problem but have rather different objectives [12–14]. In such a game, a moving robot's objective is to capture a running target in the field. For example, in [12], a team of pursuers traverse the edges of a graph G to capture a fugitive who has complete knowledge of the pursuers' locations. The problem is to determine the smallest number of pursuers needed to guarantee capture of the fugitive. In [13], the problem of finding such a minimum is proven to be NP-complete for general graphs while linear time solutions exist for trees. While robot sensory is not considered in the aforementioned work, in [14], the authors consider pursuers with sensing modules. Based on sensed strengths of an evader signal, pursuers adaptively determine their directions to maximize the probability of finding the evader. Overall, the objective of these studies is to capture a known target in the field. They often assume complete knowledge, albeit with some error, at the mobile nodes. They also do not address the problem of detecting the presence of targets or other common sensor network applications such as field or boundary estimation.

There has been some recent work in fidelity and feature driven adaptive mobile sampling [24, 25]. These approaches are based on sequential sampling criteria that are closely related to "active learning" procedures that have been proposed in the neural networks literature [26]. There is also recent work on adaptive sensor activation for minimax-optimal field and boundary estimation [27, 28].

Exposure in mobile sensor networks with planned mobility is studied in [5]. A similar collaborative sensing approach is exploited as that used in this paper except each node follows a scheduled route. The authors formally define exposure in such mobile sensor networks and propose a time expansion method to evaluate the exposure with the presence of obstacles. Our work is based on a different mobility model. Since there is no prior knowledge about the routes of UM nodes, exposure of the network cannot be computed using the time expansion method.

In [29], a design frame work is proposed for uncoordinated mobile sensing based on profile estimation. The performance and design tradeoffs are studied through simulations for point target detection, field estimation, and edge detection. Experiments of collecting data by sensors mounted on random roaming zebras are studied in [30]. The data are routed peer to peer and eventually collected by researchers periodically driving by or flying over.

Recently, a number of studies explored the usage of different movement strategies of mobile nodes to enhance operations such as packet delivery [3] and power conservation [4] in sensor networks or ad hoc wireless networks. In [2], power efficiency of stationary sensors for data collection is improved using a number of random roaming entities called data MULEs which relay the data collected by stationary sensors to wired access points. Performance such as rate of successful data relaying and required buffer capacities on the data MULEs are investigated. This work is related to ours in that the network also employs mobile nodes with uncoordinated mobility.

6. CONCLUSION

This paper investigates the detection latency in a mobile sensor network with UM nodes. The network is designed to detect the presence/absence of a target in the region using a collaborative sensing architecture. An analytic model based on Markov chain is developed to evaluate the detection latency. The estimation obtained by the analytic method is shown to well match the simulation results even when the number of nodes is small.

Comparisons between detection latencies of mobile sensor networks and conventional stationary sensor networks are also presented. A promising aspect of mobile sensor networks is that the worst-case detection latency is much shorter than that of stationary sensor networks. In particular, the assessment provides a quantitative comparison for the cost of mobile and stationary sensor networks.

This work addresses the problem of detecting an idling target in the monitored region. It is sufficient for some cases such as detecting a bomb or a heat source. However, many applications deal with traversing targets such as vehicles or human beings. Investigating the performance of detecting a traversing target needs to be further explored.

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