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Leveraging data fusion to improve barrier coverage in wireless sensor networks

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Abstract

Intruder detection and border surveillance are amongst the most promising applications of wireless sensor networks. Barrier coverage formulates these problems as constructing barriers in a long-thin region to detect intruders that cross the region. Existing studies on this topic are not only based on simplistic binary sensing model but also neglect the collaboration employed in many systems. In this paper, we propose a solution which exploits the collaboration of sensors to improve the performance of barrier coverage under probabilistic sensing model. First, the network width requirement, the sensor density and the number of barriers are derived under data fusion model when sensors are randomly distributed. Then, we present an efficient algorithm to construct barriers with a small number of sensors. The theoretical comparison shows that our solution can greatly improve barrier coverage via collaboration of sensors. We also conduct extensive simulations to demonstrate the effectiveness of our solution.

Keywords wireless sensor networks, coverage, deployment, data fusion, percolation theory

1 Introduction

The growing techniques of wireless sensor networks have enabled people to observe the physical world more closely. Detecting intruders and surveilling borders are amongst the most promising applications. In such applications, lots of sensors are deployed along the boundaries of protected areas to perform intruder detection, as illustrated in Fig. 1. Typical protected areas include nuclear fuel factories, airport runway pavements, military restricted area, mountain landslide area, and critical infrastructures. The problem of reducing the number of deployed sensors while achieving sufficient detection accuracy is of vital importance to enable such applications.

Barrier coverage [1] has been proposed to formulate this problem as constructing barriers, each of which can detect the intruder at least once no matter which crossing path the intruder follows. Lots of studies have investigated various aspects of barrier coverage. The minimum number of sensors needed to provide barrier coverage is derived in Refs. [1–3]. The critical dimension for achieving barrier coverage is analyzed in Ref. [3]. In sensor scarcity case, node mobility is exploited to enhance barrier coverage [4]. Solutions [5–6] are designed to construct barriers for camera sensor network, which is quite different from scalar sensor networks. Multi-round deployment strategy is analyzed in Ref. [7]. One-way barrier coverage is explored in Ref. [8]. Coverage preserving and scheduling algorithms are designed in Ref. [3].

However, existing studies exhibit their inefficiency in two aspects. First, all of these studies are based on the simplistic binary disc sensing model, which cannot capture the stochastic nature of sensing capability of real sensors [9]. Second, they neglect the collaboration amongst sensors. In fact, various collaborative signal processing techniques have been adopted to improve performance in many systems [10–13], but previous studies on barrier coverage still assume that the sensors perform detection independently. Although some work has proposed to use data fusion to improve the performance of point coverage [14–15], but their results cannot not be

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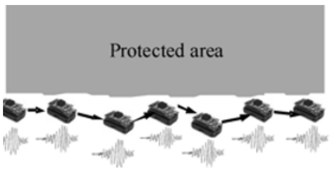
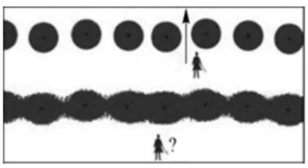
directly used to resolve the problem of barrier coverage which is distinct from point coverage. Recently, a contributive work [16] explores the adoption of data fusion under probabilistic sensing model, leading to a distinct performance improvement of barrier coverage. But their work mainly focuses on weak barrier coverage which can only guarantee the detection of targets that follow perpendicular crossing paths. The more challenging problem of strong barrier coverage in networks adopting data fusion still remains open. Since strong barrier coverage can guarantee the detection of targets no matter which path it follows, it reflects better the real detection capability of a system.

In this paper, we take the first step in exploring performance of strong barrier coverage after exploiting data fusion under probabilistic sensing model. However, this problem is rather challenging. Fig. 1(b) gives snapshot of covered area before and after employment of data fusion respectively. As can be seen that collaboration amongst sensors greatly complicates the analysis of barrier coverage. This is because whether a point is covered no longer depends only on the position of the nearest sensor, but on both the number of collaborating sensors and the position of all the collaborating sensors.



(a) An example of intruder detection system



(b) Without data fusion, no barrier exists in the upper case; while a barrier is formed in the lower case that employs data fusion

Fig. 1 Illustrations of an intruder detection system and barrier coverage

We address the above challenge as follows. Firstly, we analyze the maximal distance between neighboring sensors in a barrier before and after data fusion. Secondly, based on percolation theory, we analyze the network width and sensor density requirement for barrier coverage, and the relationship amongst the number of barriers, the network width, the sensor density, and the number of collaborating sensors when sensors are randomly deployed. Finally, an efficient algorithm is designed to construct barriers.

The rest of the paper is organized as follows. Sect. 2 presents the models and problem definition. In Sect. 3, we first analyze the maximal distance between neighboring sensors, and then we prove deployment requirement and barrier quantity of barrier coverage under data fusion model. Finally, a barrier construction algorithm is presented. Simulation results are presented in Sect. 4, and Sect. 5 concludes the paper.

2 Models and problem definition

2.1 System model

We consider a set of N sensors uniformly and independently distributed in a two-dimensional rectangle of length l and width w. As proved in Ref. [17], such an uniform deployment is essentially a Poisson process of intensity λ, i.e., the ratio of N to the area of the region. We use $\| R \|$ to represent the area of any subregion R. So, the number of sensors in subregion R, $N(R)$, is Poisson distributed with mean $\lambda \| R \|$. Also, we assume the positions of sensor are known.

We define a barrier as a subset of sensors which can detect any target attempting to cross the rectangle along any crossing path. To facilitate discussion, we assume that the identity of sensors are sorted from left to right and denote the sensor with id i as s_i. Two sensors in a barrier are said to be neighboring sensors if they have identity with a difference of 1. The detection line represents the concatenation of all straight line segments connecting any two neighboring nodes. Fig. 2 is an illustration of these concepts. All nodes in the example form a barrier.

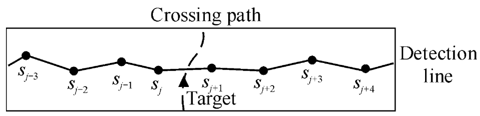


Fig. 2 Illustrations of some concepts

Suppose the target t appears in the network, we assume the signal strength, $x_i(t)$, at the position of sensor s_i is [18]:

$$x_i(t) = \begin{cases} S; & (s_i,t) < d_0 \\ \dfrac{S}{\left(\dfrac{d(s_i,t)}{d_0}\right)^{\gamma}}; & d(s_i,t) \geqslant d_0 \end{cases} \tag{1}$$

where S is the original signal amplitude of the target, d_0 is a small constant, and $d(s_i,t)$ is the distance between the sensor s_i and the target t. In addition, γ is the signal decay exponent, typical between 1 and 5. Since d_0 can be chosen arbitrarily small, for convenience, we only concentrate on the case $d(s_i, t)>d_0$ in latter derivations.

Depending on the hypothesis whether the target is present H_1 or not H_0, the measurement of sensor s_i, denoted by y_i, is given by

$$\begin{cases} H_0: y_i = n_i \\ H_1: y_i = x_i(t) + n_i \end{cases} \tag{2}$$

where n_i is additive random noise and $x_i(t)$ is the decayed signal strength described above. We assume the noise n_i at each sensor independently and identically follows a normal distribution of mean μ_i and variance σ^2, i.e., $n_i \sim N(\mu_i, \sigma^2)$.

2.2 Detection model

We assume there is a fusion head collecting the measurements of multiple sensors near the possible target. Then, it compares the weighted sum of sensor measurements $\sum w_i y_i$, where w_i is the weight of s_i, against a predefine threshold T. It decides that a target is present if $\sum w_i y_i \geqslant T$; otherwise, it decides that no target is present. Note that only sensors in the same barrier should participate in a detection process, since barriers may be scheduled to work in turn.

For such fusion scheme of weighted sum stated above, G. Xing et al. [14] proved that the optimal fusion rule is to compare the weighted sum $Y^* = \sum \{[x_i(t)]/\sigma\} y_i$ against a threshold T. However, since the sensor's measurement contains both the signal $x_i(t)$ and the noise n_i, it is impossible to derive the weight $[x_i(t)]/\sigma$. In this paper, we adopt a constant weight fusion rule. Suppose sensor s_j and s_{j+1} are the two sensors connected by the line segment $L(s_j,s_{j+1})$ which is the line segment in the detection line nearest to the possible target t. Sensors with smaller identity than sensor s_j (or with larger identity than sensor s_{j+1}) usually have larger distance from the target than sensor s_j (or sensor s_{j+1}), as illustrated in Fig. 2. Inspired by this observation, we set the weight of the ith sensor, i.e., w_i, on the left/right of $L(s_j,s_{j+1})$ to $1/(2i-1)^\gamma$. For example, the weight of the sensor s_j and s_{j+1} in Fig. 2 is $1/(2-1)^\gamma$, the weight of the sensor s_{j-1} and s_{j+2} is $1/(4-1)^\gamma$. Moreover, we only allow h sensors on each side of $L(s_j,s_{j+1})$ to participate in a data fusion process in order to exclude the measurements with low signal noise ratio (SNR)s from data fusion.

In summary, the weighted sum of sensor measurements is

$$Y = \sum_{i=1}^{h} w_i(y_{li} + y_{ri}) = \sum_{i=1}^{h} \frac{y_{li} + y_{ri}}{(2i-1)^\gamma} \tag{3}$$

where $w_i = 1/(2i-1)^\gamma$ and y_{li} (or y_{ri}) is the measurement of the ith sensor in the barrier on the left (or right) side of the target. To assist the decision making process, we utilize existing signal source estimation methods to find the line segment nearest to the possible target, which is also adopted in Ref. [14]. Apparently, if more efficient fusion models are used, the results of this paper still hold.

2.3 Problem definition

Detection probability $P_D(p)$ is the probability of detection of a target when the target is present at position p. False alarm probability P_F is the probability of detection of a target when there is no target, so it is location independent.

Definition 1 ((α, β)-coverage) Given two constants α and β, a point p in the rectangle is (α, β)-covered iff the false alarm probability P_F and detection probability $P_D(p)$ satisfy

$$\left.\begin{array}{l} P_F \leqslant \alpha \\ P_D(p) \geqslant \beta \end{array}\right\} \tag{4}$$

Definition 2 (Barrier coverage) A network is said to be barrier covered if there exists a barrier such that for any crossing path, there are at least one point on the path that will be (α, β)-covered by sensors in the barrier.

If k disjoint barriers exist in a network, the network is said to be k barrier covered. For convenience, we use coverage to refer to (α, β)-coverage. Whether a barrier is formed depends on the shape of the covered area of sensors. The latter depends not only on the number of sensors but also the relative positions of sensors. Therefore, it is rather difficult to precisely analyze the relationship between the density of sensors and barrier coverage. Hence, we make an assumption to derive a lower bound of the impact of data fusion.

Assumption AS The maximal distance between any neighboring sensors in a barrier is no larger than a value d, which satisfies the condition that a barrier is still formed when all sensors are placed at an interval of d along a straight line.

The purpose of this assumption is only to simplify our analysis. Relaxation of this assumption will lead to better results. And all results derived in this paper still hold.

3 Fusion barrier coverage

In this section, we analyze the maximal distance of neighboring sensors, deployment requirement and barrier quantity when data fusion is adopted. Moreover, we present the barrier construction algorithm.

3.1 Analysis of maximal distance

Now, we derive the maximal distance d satisfying the condition that a barrier is formed when all sensors are placed at an interval no larger than d.

3.1.1 Non-collaborative barrier coverage

In non-collaborative barrier coverage, each sensor performs target detection without collaboration. The optimal Bayesian fusion rule for a single sensor is rather straightforward [19]. For any sensor s_i, it makes a decision that a target appears if y_i is larger than a predefined threshold T_1; otherwise, it makes a decision that no target appears. So, we get

$$\left.\begin{aligned} &P_F = P(n_i \geqslant T_1) \leqslant \alpha \\ &\Rightarrow \quad 1 - F_N(T_1) \leqslant \alpha \\ &\Rightarrow \quad T_1 \geqslant F_N^{-1}(1-\alpha) \end{aligned}\right\} \tag{5}$$

where $F_N(\cdot)$ is the cumulative distribution function of noise n_i. Moreover, the detection probability of any point p is given by

$$P_D(p) = P[n_i + x_i(p) \geqslant T_1) = P[n_i \geqslant T_1 - x_i(p)] = 1 - F_N[T_1 - x_i(p)] \geqslant \beta \tag{6}$$

$$\Rightarrow \quad x_i(p) \geqslant T_1 - F_N^{-1}(1-\beta) \tag{7}$$

From Eq. (6), we know that $P_D(p)$ is a nonincreasing function of T_1, since $F_N(\cdot)$ is a nondecreasing function. In order to maximize detection probability $P_D(p)$ and guarantee that false alarm probability is no larger than α, we should set the optimal value of T_1 to the minimal value of T_1 in Inequality (5), i.e., $T_1^* = F_N^{-1}(1-\alpha)$. Replacing T_1 by T_1^* in Inequality (7), we can infer that the maximal coverage region of s_i is:

$$R_{\text{cov}} = p \mid x_i(p) \geqslant T_1^* - F_N^{-1}(1-\beta) = p \mid x_i(p) \geqslant F_N^{-1}(1-\alpha) - F_N^{-1}(1-\beta) \tag{8}$$

According to the expression of $x_i(p)$ and the relationship $F_N^{-1}(q) = \mu + \sigma\, \Phi^{-1}(q)$, where $\Phi^{-1}(\cdot)$ is the inverse of cumulative distribution function of standard normal distribution, the above equation can be transformed into

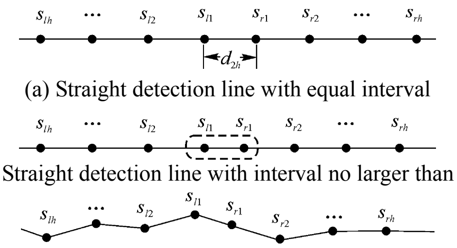
$$R_{\text{cov}} = \left\{ p \,\middle|\, \frac{S}{\left(d\,\dfrac{(s_i, p)}{d_0}\right)^{\gamma}} \geqslant \sigma[\Phi^{-1}(1-\alpha) - \Phi^{-1}(1-\beta)] \equiv A \right\} = \left\{ p \mid d(s_i, p) \leqslant d_0 \left(\frac{S}{A}\right)^{1/\gamma} \right\}$$

So, the sensing radius of any sensor s_i is $d_0(S/A)^{1/\gamma}$, and thus the maximal distance between neighboring sensors, denoted by d_1, in a barrier is no larger than 2 $d_0(S/A)^{1/\gamma}$.

3.1.2 Fusion barrier coverage

As described in Sect. 2.2, the data fusion scheme compares the weighted sum of $2h$ senor measurements, i.e., $Y = \sum_{i=1}^{h} w_i (y_{li} + y_{ri})$, with a predefined threshold in order to decide whether a target appears. Here, we denote the predefined threshold as T_{2h}. In the following discussion, we will prove that if the maximal distance between neighboring sensors in a barrier is no larger than a specific value d_{2h}, then the detection line of the barrier is covered.

First, we start from straight detection lines on which all sensors are placed at an interval of d_{2h}, as shown in Fig. 3(a). Then, we analyze general detection lines on which neighboring sensors are placed with distance no larger than d_{2h}, as shown in Figs. 3(b) and (c). In the following discussion, we temporarily ignore the boundary effects which will be dealt with later.



(a) Straight detection line with equal interval

(b) Straight detection line with interval no larger than d_{2h}

(c) General detection line with interval no larger than d_{2h}

Fig. 3 Some detection lines satisfying Assumption AS

Case A Straight detection line with equal interval

Now, we analyze the straight detection lines with sensors equally spaced at an interval of d_{2h}. To facilitate discussion, we suppose identity of the sensors is the same shown in Fig. 3(a). First, we analyze the necessary and sufficient condition for the midpoint of line segment $L(s_{l1}, s_{r1})$ being covered. Apparently, the random variable function

$\sum_{i=1}^{h} w_i(n_{li}+n_{ri}) \sim N\left(2\mu\sum_{i=1}^{h} w_i,\ 2\sigma^2\sum_{i=1}^{h} w_i^2\right)$.

If a barrier is formed, the false alarm probability is

$$P_F = P\left(\sum_{i=1}^{h} w_i(n_{li}+n_{ri}) \geqslant T_{2h}\right) \leqslant \alpha$$

$$1-F(T_{2h}) \leqslant \alpha \Rightarrow T_{2h} \geqslant F^{-1}(1-\alpha)$$

where $F(\cdot)$ is the cumulative distribution function of $\sum_{i=1}^{h} w_i(n_{li}+n_{ri})$. Similar to the choice of T_1, we set T_{2h} to $F^{-1}(1-\alpha)$, denoted by T_{2h}^*. Accordingly, the detection probability of a point p is given by

$$P_D(p) = P\left\{\sum_{i=1}^{h} w_i[x_{li}(p)+n_{li}+x_{ri}(p)+n_{ri}] \geqslant T_{2h}\right\} =$$
$$1-F\left\{T_{2h}-\sum_{i=1}^{h} w_i[x_{li}(p)+x_{ri}(p)]\right\} \geqslant \beta \Rightarrow$$
$$\sum_{i=1}^{h} w_i[x_{li}(p)+x_{ri}(p)] \geqslant T_{2h}-F^{-1}(1-\beta)$$

Replacing T_{2h} by T_{2h}^*, we have the necessary and sufficient condition for a point p being covered:

$$\sum_{i=1}^{h} w_i[x_{li}(p)+x_{ri}(p)] \geqslant F^{-1}(1-\alpha)-F^{-1}(1-\beta) \geqslant$$
$$\sqrt{2\sum_{i=1}^{h} w_i^2}\,\sigma[\Phi^{-1}(1-\alpha)-\Phi^{-1}(1-\beta)] = A\cdot B \tag{9}$$

where $B=\sqrt{2\sum_{i=1}^{h} w_i^2}$. Let $L(s_{l1},s_{r1})$ be any line segment on the detection line and p the midpoint of $L(s_{l1},s_{r1})$. According to Inequality (9), we have the necessary and sufficient condition for point p being covered:

$$\sum_{i=1}^{h} w_i[x_{li}(p)+x_{ri}(p)] = \sum_{i=1}^{h} 2\frac{w_i S}{\left[\dfrac{(2i-1)d_{2h}}{(2d_0)}\right]^{\gamma}} \geqslant A\cdot B \Rightarrow$$
$$d_{2h} \leqslant 2d_0\left(\frac{S\cdot B}{A}\right)^{1/\gamma} \tag{10}$$

In order to maximize the distance, we set d_{2h} to $2d_0(S\cdot B/A)^{1/\gamma}$.

We proceed to show that the midpoints between any neighboring sensors must be covered if a barrier is formed.

Lemma 1 If sensors are equally spaced at an interval of d_{2h} along a straight line, the midpoints between any neighboring sensors being covered is a necessary condition for formation of a barrier.

Proof Suppose a barrier is formed. Without loss of generality, we assume that the midpoint p of line segment $L(s_{l1},s_{r1})$ is not covered. According to Inequality (9), we get

$$\sum_{i=1}^{h} w_i[x_{li}(p)+x_{ri}(p)] < A\cdot B$$

Consider any other point q on the line that is perpendicular to $L(s_{l1},s_{r1})$ and intersects with $L(s_{l1},s_{r1})$ at point p. Since $d(q,s_{li}) > d(p,s_{li})$ and $d(q,s_{ri}) > d(p,s_{ri})$, we have

$$\sum_{i=1}^{h} w_i[x_{li}(q)+x_{ri}(q)] < \sum_{i=1}^{h} w_i[x_{li}(p)+x_{ri}(p)] < A\cdot B$$

Hence, any other point q is not covered. Thus, no barrier can be formed, which contradicts the assumption. The lemma is proved.

Lemma 2 The sufficient condition of formation of a barrier is that all midpoints between neighboring sensors are covered, for a sensor deployment satisfying the following conditions: 1) Assumption AS holds; 2) the detection line is straight; 3) the distance between any neighboring sensors is d_{2h}.

Proof Let q be any point on a line segment $L(s_{l1},s_{r1})$ and p be the midpoint. We use Δd to represent the distance between q and p.

$$\sum_{i=1}^{h} w_i[x_{li}(q)+x_{ri}(q)]$$
$$\sum_{i=1}^{h} w_i\left\{\frac{Sd_0^{\gamma}}{\left[\dfrac{(2i-1)d_{2h}}{2+\Delta d}\right]^{\gamma}}+\frac{Sd_0^{\gamma}}{\left[\dfrac{(2i-1)d_{2h}}{2-\Delta d}\right]^{\gamma}}\right\} \geqslant$$
$$\sum_{i=1}^{h}\frac{2w_i Sd_0^{\gamma}}{[(2i-1)d_{2h}/2]^{\gamma}}.$$

The last inequality holds because for any positive constant C, the function $f(x)=1/(C+x)^{\gamma}+1/(C-x)^{\gamma}$ is monotonically increasing on the range [0, C]. We combine this inequality with Inequality (10) to deduce that

$$\sum_{i=1}^{h} w_i[x_{li}(q)+x_{ri}(q)] \geqslant A\cdot B$$

Hence, any point q is covered according to Inquality (9). This completes the proof.

With Lemma 1, and 2, we have the following theorem.

Theorem 1 The detection line is covered and a barrier is formed if the sensor deployment satisfies: 1) Assumption AS holds; 2) the detection line is a straight line; 3) the distance between any neighboring sensors is d_{2h}.

Case B General detection line

Now, we consider the general detection lines on which neighboring sensors are placed with distance no larger than d_{2h}, as shown in Fig. 3(b) and Fig. 3(c). In other words, we relax the assumption 2) and 3) in Theorem 1.

Theorem 2 If a sensor deployment satisfies the condition that the distance between any neighboring sensors is no larger than d_{2h}, the detection line is covered and a barrier is formed.

Proof We prove this by two steps.

1) The detection line is a straight line, see Fig. 4(a). We can construct any such a deployment from a deployment satisfying the three conditions of Theorem 1 by contracting the detection line, i.e., moving sensors closer. In each contraction, the weighted sum of the signal, $\sum_{i=1}^{h} w_i[x_{li}(p)+x_{ri}(p)]$, of any point p on the detection line does not decrease. Since a detection line satisfying the three conditions of Theorem 1 is covered, the detection line is still covered after each contraction.

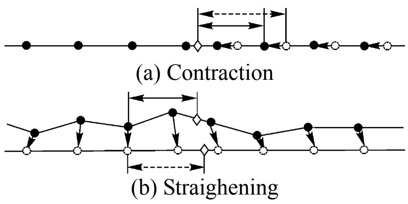


Fig. 4 Illustration of detection line transformation

2) The detection line is not a straight line, see Fig. 4(b). We can straighten any such a detection line. After the detection line is straightened, the distance from any point p on the detection line to h sensors on each side does not decrease. Thus, the weighted sum of the signal does not increase. We can infer that the weighted sum of point p on the original detection line is no less than that of point p on the straightened detection line. Apparently, the straightened detection line satisfies the conditions of step 1, so it is covered. Thus, the original detection line is also covered.

Therefore, the theorem is proved.

Now, we know the maximal distance between neighboring sensors is prolonged after adoption of data fusion. The improvement ratio of the maximal distance is given by

$$I \equiv \frac{d_{2h}}{d_1} = \frac{2d_0\left(S\cdot\dfrac{B}{A}\right)^{1/\gamma}}{2d_0\left(\dfrac{S}{A}\right)^{1/\gamma}} = B^{1/\gamma} = \left(2\sum_{i=1}^{h}\frac{1}{(2i-1)^{2\gamma}}\right)^{1/(2\gamma)}$$

It is clear that the improvement ratio increases with h and decreases with γ. This means that when more sensors collaborate on performing target detection, the number of sensors required to form a barrier will be reduced.

3.2 Deployment requirements and barrier quantity

In this subsection, we first prove the critical dimension for fusion barrier coverage by converting the problem to a bond percolation problem. Then, we derive the relationship amongst number of barriers, network width, sensor density, and number of collaborating sensors. The boundary effect will be discussed at the end of this subsection.

We divide the network area into squares of side length $d_{2h}/(2\sqrt{2})$ as depicted in Fig. 5(a). Since the random deployment of sensors follows Poisson distribution as described in Sect. 2.1, the probability that a square contains at least one sensor is given by

$$P = 1-\mathrm{e}^{-\gamma_c d_{2h}^2/8} \equiv p \tag{11}$$

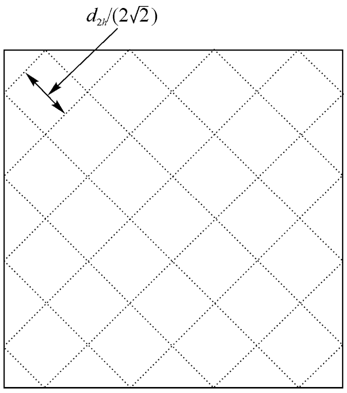
where γ_c is the sensor density, P is a square contains sensors.

We define that a square is open if it contains at least one sensor; otherwise, it is closed. Then, we draw a horizontal edge or a vertical edge across each square as shown in Fig. 5(b). Each intersection point of the edges is called a vertex. A bond percolation model is constructed since a lattice is obtained whose edges are open, independently with each other, with probability p. The existence of a horizontal open path in the lattice means the existence of a barrier in the network, since two connected open edges means existence of at least two sensors within distance d_{2h} from each other.

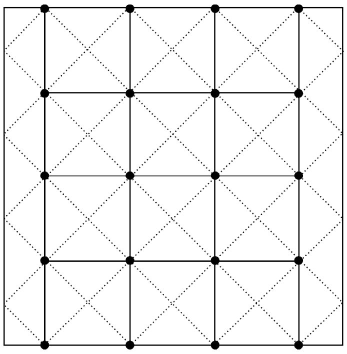
We construct a virtual sensing disc of radius $d_{2h}/2$ for every sensor in the network. Then, we get the width requirement for barrier coverage under probabilistic sensing model based on the results proved in Ref. [3] under disc model:

Theorem 3 If $w=\Omega(\lg l)$, the network is barrier covered when the sensor density λ reaches a certain value. If $w=o(\lg l)$, the network cannot be barrier covered no matter what the sensor density is.

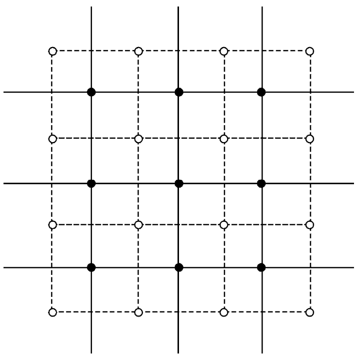
Based on the density requirement derived under disc sensing model in Ref. [3], we can derive the required density under probabilistic sensing models. Specifically, for non-collaborative sensing model, if sensor density $\lambda_1 > 8(\lg 6+2/\kappa)/d_1^2$, where κ is a positive constant, there exist barriers in the network. For data fusion sensing model, if sensor density of the network $\lambda_{2h} > 8(\lg 6 + 2/\kappa)/d_{2h}^2 = 8(\lg 6 + 2/\kappa)/(I^2 d_1^2)$, barriers exist in the network. It is clear that the required density is reduced by I^2 times when data fusion is employed.



(a) Division of the network area



(b) Construction of bond percolation model



(c) Construction of dual lattice

Fig. 5 Construction of the bond percolation model

Apart from the sensor density and maximal distance between neighbors, the width of network is also a key factor in the formation of barriers, as shown by Theorem 3. However, its influence cannot be reflected by the density requirement and number of barriers proved in Ref. [3]. Therefore, we derive new results which take into account network width.

Before giving the main result, we introduce some concepts. A realization means the set of resulted edges of a bond percolation model. We define the dual lattice of a lattice by placing a vertex in each square and add an edge between two vertices only when the corresponding squares share an edge in the lattice. See Fig. 5(c). In the dual lattice, we also construct the dual of a realization by adding an open edge in the dual if and only if the crossed edge in the original lattice is closed. In this way, we have constructed another bond percolation model. We use n and m to represent the number of vertices in a row and in a column respectively. Then, $n=2l/d_{2h}$ and $m=2w/d_{2h}$. Based on this model, the follow theorem can be proved.

Theorem 4 Suppose $m/\lg n \to a$ as $n \to \infty$, and $a>0$. If $\lambda_{2h} > \left(8/d_{2h}^2\right)\lg\left[3/\left(2e^{-1/a}-1\right)\right]$, then

$$\lim_{n\to\infty} P\,[\text{number of barriers} \leqslant \delta \lg n] = 0$$

where $\delta = \left\{a\lg[2/(3e^{\lambda_{2h}d_{2h}^2/8}+1)]-1\right\}\Big/\left\{2\lg[3/(1-e^{-1/a})]\right\}$.

The proof of the theorem is given in the appendix.

The result above reveals the relationship amongst the sensor density requirement, the network width, the number of sensors participating in data fusion (through d_{2h}) and the relationship amongst the number of barriers, sensor density, the network width, and the number of participating sensors.

In fact, we should expand the length of the original network by a small constant at both ends to ensure the existence of h sensors in each barrier beyond the boundary of network. Apparently, the expansion will not change the logarithmic relationship between the width and the length of the network, and thus will not contaminate the correctness of the result.

3.3 Fusion barrier construction algorithm

Network engineers can utilize the derived information in the previous subsection to deploy networks in order to meet specific requirement of barrier coverage for various applications. However, we still need an efficient algorithm to construct barriers for randomly deployed sensor networks. Such an algorithm is indispensable in both the initialization phase and barrier restoration phase, since barriers may be corrupted after some nodes run out of energy.

As proved in Theorem 2, sensors form a barrier when the distance between any two neighboring sensors is no larger than d_{2h}. Hence, we can transform the barrier construction problem into the well-known maximum flow problem that is to find the maximum feasible flow through a single-source, single-destination flow network. Algorithm 1 gives the procedure of the barrier construction algorithm.

Construction of the coverage graph needs $O(V^2)$ time and the maximum flow algorithm terminates in $O(VE^2)$ time. Hence, the computational complexity of barrier construction algorithm is $O(V^2+VE^2)$, which is efficient considering the difficulty of the problem.

Algorithm 1 Barrier Construction Algorithm

Construct a coverage graph $G=(V,E)$, in which V contains all sensor nodes, $(s_1,s_2)\in E$ if $d(s_1,s_2)\leqslant d_{2h}$ for any two sensors s_1 and s_2;

Add two virtual nodes u and v to V;

Add an edge (u, s_i) to E if the distance between s_i and extended left boundary is smaller than d_{2h};

Add an edge (s_i, v) to E if the distance between s_i and extended right boundary is smaller than d_{2h};

Set the capacity of all edges to 1;

Call a maximum flow algorithm (e.g. Ford-Fulkerson [20]) to find k disjoint paths between u and v in G:

u-path$_1$-v, u-path$_2$-v,… , u-path$_k$-v;

Return path$_1$, path$_2$,… , path$_k$ as k barriers;

4 Simulation

In this section, we evaluate the impact of data fusion on the coverage area, the probability of barrier coverage, sensor density requirement, number of barriers, and network lifetime by extensive simulations. The results will help us get a sense of real benefits of our solution. We compare the fusion barrier coverage with the non-collaborative barrier coverage (NoFusion) and an approach proposed in Ref. [16] which is designed to provide weak barrier coverage. Since the approach proposed in Ref. [16] is originally developed to guarantee 1 weak barrier coverage, we improve the approach to provide k weak barrier coverage and name it WeakBar.

Since we cannot simulate networks of infinite length, the network length is configured to 1 200 units. The upper bound of false detection probability α is set to 0.05, and the lower bound of detection probability β is set to 0.9. Also, we set S to 30, γ to 1, and d_0 to 0.2 units. We assume the noise n_i follows a normal distribution $N(0, 1/2)$. Due to space limitation, we only give some important results.

4.1 Barrier coverage performance

First, we compare coverage area of fusion barrier coverage with NoFusion and WeakBar. Fig. 6 shows the results of a typical topology. In all schemes, NoFusion covers the smallest area. WeakBar is designed to detect any target that follows a perpendicular crossing path, so no barrier is formed in WeakBar in many cases, as can be seen in Fig. 6(b). Hence, a target can easily cross the network along a line that is not perpendicular without being detected. In contrast, a barrier is built up in our data fusion scheme, as shown in Fig. 6(c). The built barrier can guarantee detection of target no matter which crossing path the target follows.

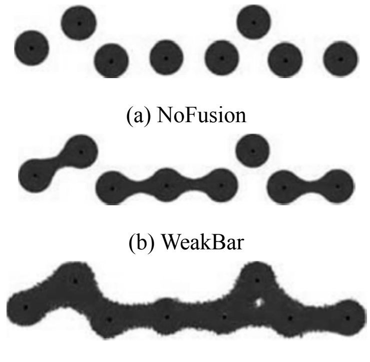


Fig. 6 Coverage area of different schemes

Fig. 7 plots the probability of barrier coverage in a network of width 30 units. The probability in three schemes increases with the number of sensors, as expected. Moreover, we can see that fusion barrier coverage greatly outperforms NoFusion and WeakBar. When h=3, the fusion barrier coverage saves about 45.21% nodes to achieve barrier coverage with probability 1, as compared to WeakBar. This is because collaboration enhances detection capability of sensors. Furthermore, the probability increases with h, since more and more information are used to detect target when h increases.

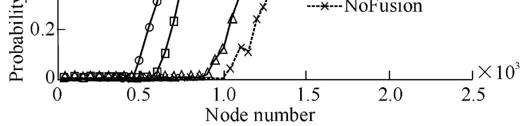


Fig. 7 Probability of barrier coverage vs. node number

For h=3 and different width of the network, as shown in Fig. 8, the critical density requirement of all three schemes decreases with the increase in the network width. This is because a crossing path has more chance to intersect the coverage area of sensors in a wide network than in a narrow one. Moreover, fusion barrier coverage outperforms the other two schemes. Compared with WeakBar and NoFusion, the required density in fusion scheme to achieve barrier coverage is reduced by about 40.91% and 49.43% on average respectively.

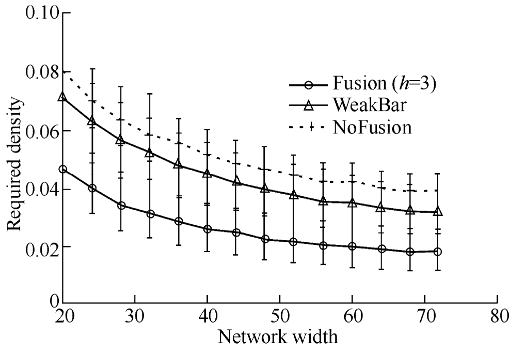


Fig. 8 Density requirement vs. network width

Fig. 9 plots the number of barriers as a function of number of sensors when the network width is 30 units. Also, we set λ to 0.08 and evaluate the impact of network width on the number of barriers.

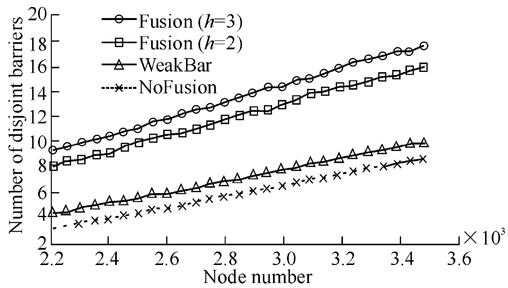


Fig. 9 Number of disjoint barriers vs. number of sensors

The results are shown in Fig. 10. We can observe that fusion barrier coverage greatly increases the number of formed barriers as compared to WeakBar and NoFusion. Specifically, when h=3, the number of barriers is nearly doubled by fusion barrier coverage in both sets of experiment. This is because barrier coverage based on data fusion cooperates to detect target, allowing a longer distance between neighboring sensors in a barrier than without it. Thus, the opportunity of sensors to form barriers increases.

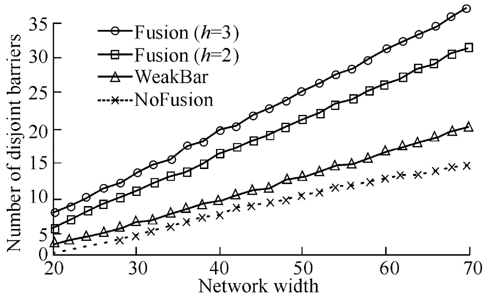


Fig. 10 Number of disjoint barriers vs. network width

4.2 Network lifetime

Data fusion improves barrier coverage at the expense of extra energy consumption for information change between sensors. So, it is beneficial to explore the overall network lifetime. We use a transmission range R of 15 units. We use a simple method to find the nearest line segment to the possible target. All nodes have sensor measurement larger than $S/(R/2d_0)^{\gamma}$ broadcast sensors. Then, nodes within the distance R/2 from the possible target will broadcast and overhear each others' measurement. The line segment nearest to the estimated signal source is computed as the nearest one. Then, the left sensor on the line segment collects 2h sensor measurement and make decision of target detection. We fix the number of sensors to 1800 and the network only needs to 1 barrier covered. In all schemes, only sensors that form the barrier stay active. When the barrier is corrupted after a node runs out of energy, a new barrier is constructed. We assume that the target appears rarely in the networks. The power consumption of receiving and transmitting (Telosb datasheet. http://www.xbow.com/) is set to 70 mW, and that of sensing is set to 2.5 mW, which is the power consumption of a typical low-power acoustic sensor (MP34DB01 datasheet. http://www.st.com/). We omit the routing overhead.

Fig. 11 plots lifetime for different sensing frequencies, i.e., 0.25 Hz, 0.5 Hz, 1 Hz, and 2 Hz. The results are normalized to the lifetime of NoFusion scheme with sensing frequency of 0.25 Hz. As shown in the figure, fusion barrier coverage outperforms WeakBar and NoFusion in all considered cases. This means that the reduction of active nodes by data fusion prolongs the network lifetime despite some overhead of collaboration. Moreover, the advantage of fusion barrier coverage decreases as the sensing frequency increases. In addition, we find that when the sensing frequency is high, an h that is larger than 3 almost leads to the the same performance as when $h = 2$. This implies that data fusion scheme works the best in sensor networks with low sensing frequency. Also, when the sensing frequency is high, an h of 2 or 3 may be sufficient since larger h will not result in distinct improvement of network lifetime.

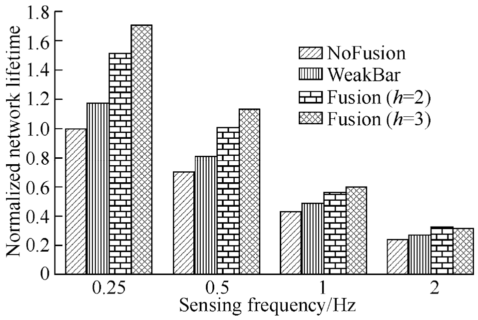


Fig. 11 Network lifetime vs. sensing frequency

5 Conclusions

In this paper, we propose a solution which exploits data fusion to improve the performance of barrier coverage. We derive the required network width, the sensor density and the number of barriers under data fusion model when sensors are randomly deployed. Moreover, an efficient algorithm is designed to construct barriers. The theoretical comparison indicates that our solution can greatly improve barrier coverage. The effectiveness of our solution is also verified by extensive simulations. In the future, we plan to analyze the connectivity and coverage issues jointly when data fusion is adopted. Furthermore, we will implement the proposed data fusion scheme on sensor nodes equipped with acoustic and vibration sensors.

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Appendix A Proof of Theorem 4

In order to prove Theorem 4, we introduce two inequalities proved in Ref. [21] Proposition 1 and Ref. [22] Theorem 2.45 to simplify our proof. Let B_{2m} be a box of length $2m$ centered at the origin and $0 \leftrightarrow \partial B_{2m}$ be the event that the origin and the boundary of B_{2m} are connected by an open path.

Lemma 3 [21] For $p < 1/3$, $P_p(0 \leftrightarrow \partial B_{2m}) \leqslant (4/3) \cdot \mathrm{e}^{m \lg 3p}$.

An event A is said to be an increasing event if A occurs in a realization of bond percolation and A still occurs after adding any edges in the realization. $I_r(A)$ is a robust version of event A if A still occurs after changing the states of up to r arbitrary edges in a realization of bond percolation in which A occurs.

Lemma 4 [22] If A is an increasing event and r is a positive integer, then

$$1 - P_p[I_r(A)] \leqslant \left(\frac{p}{p-p'}\right)^r [1 - P_{p'}(A)] \tag{A.1}$$

when $0 \leqslant p' \leqslant p \leqslant 1$.

Proof of Theorem 4:

Proof Let N_b represent the number of disjoint horizontal open crossing paths in the lattice. We use V to represent the event that vertical crossing paths exist in the dual lattice. Existence of horizontal open crossing paths in the lattice means that there is not any vertical crossing paths in the dual lattice. Hence, for any $p' > 2/3$, we have

$$P_{p'}(N_b \geqslant 1) = 1 - P_{1-p'}(V) \tag{A.2}$$

Now, we order the vertices on the top side of the rectangle starting from the leftmost vertex to the rightmost vertex. Also, we use C_i to denote the event that there exists a crossing path starting from the ith vertex joining the top side and the bottom side. Apparently, there are at least one index i_j so that

$$P_{1-p'}(C_i) \geqslant \frac{P_{1-p'}(V)}{n+1} \tag{A.3}$$

Then, we choose the first index i_0 satisfying the above inequality as the origin of a box $B_{2a\lg n}$, see Fig. 12. Since any vertical crossing path starting from i_0 will intersect the boundary of box $B_{2a\lg n}$, we have

$$P_{1-p'}(C_i) \leqslant P_{1-p'}(0 \leftrightarrow \partial B_{2a\lg n}) \tag{A.4}$$

We combine Inequalities (13), (14) and (15) to obtain

$$P_{p'}(N_b \geqslant 1) \geqslant 1 - (n+1) P_{1-p'}(0 \leftrightarrow \partial B_{2a\lg n}) \tag{A.5}$$

With Lemma 3, we get

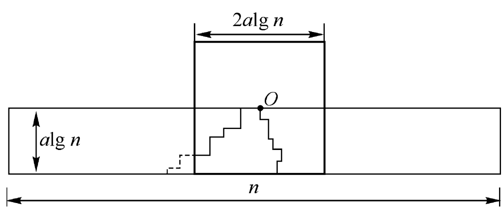

Fig. 12 Construction of Box $B_{2a\lg n}$

$$P_{p'}(N_b \geqslant 1) \geqslant 1 - \frac{4}{3}(n+1)\mathrm{e}^{a\lg n \lg[3(1-p')]} =$$
$$1 - \frac{4}{3}(n+1)n^{a\lg[3(1-p')]}$$

For any probability $p > 2/3$, let $p' = (p/2) + (1/3)$, then $2/3 < p' < p < 1$. According to Lemma 4, we get

$$1 - P_p[N_b > \delta\lg(n)] \leqslant \left[\frac{p}{p-p'}\right]^{\delta\lg n}[1 - P_{p'}(N_b \geqslant 1)] \Rightarrow$$
$$P_p[N_b \leqslant \delta\lg(n)] \leqslant \left[\frac{p}{p-p'}\right]^{\delta\lg n}\frac{4}{3}(n+1)n^{a\lg[3(1-p')]} =$$
$$n^{\delta\lg\frac{p}{p/2-1/3}}\frac{4}{3}(n+1)n^{a\lg[2-3p/2]} = \frac{4}{3}(n+1)n^{\delta\lg(\frac{p}{p/2-1/3})+a\lg[2-3p/2]}$$

When $\delta\lg\left[p/(p/2-1/3)\right] + a\lg(2-3p/2) < -1$, the right side of the above inequality approaches 0 as $n \to \infty$. If $\lambda_{2h} > (8/d_{2h}^2)\lg\left[3/(2\mathrm{e}^{-1/a}-1)\right]$, then

$$p = 1 - \mathrm{e}^{-\lambda_{2h}d_{2h}^2/8} > \frac{2}{3}\left(2 - \mathrm{e}^{-\frac{1}{a}}\right)$$

according to Eq. (11). From the above inequality, we can infer that

$$a\lg\left(2 - \frac{3p}{2}\right) < -1 \tag{A.6}$$

$$1 - p < \mathrm{e}^{\lambda_{2h}d_{2h}^2/8} \tag{A.7}$$

Since $p > (2/3)(2-\mathrm{e}^{-\frac{1}{a}})$, then

$$p/(p/2-1/3) < 1/(p/2-1/3) < 1/[(2-\mathrm{e}^{-1/a})/3 - 1/3]$$

So,

$$\delta\lg\frac{p}{\frac{p}{2}-\frac{1}{3}} < \delta\lg\frac{3}{1-\mathrm{e}^{-1/a}} \tag{A.8}$$

Then, according the assumption

$$\delta = \frac{a\lg\dfrac{2}{3\mathrm{e}^{\lambda_{2h}d_{2h}^2/8}+1} - 1}{2\lg\dfrac{3}{1-\mathrm{e}^{-1/a}}}$$

and the above inequality, we have

$$\delta\lg\frac{p}{\frac{p}{2}-\frac{1}{3}} < -\frac{a\lg\left(2-\frac{3p}{2}\right)+1}{2} \tag{A.9}$$

Hence,

$$\delta\lg\frac{p}{\frac{p}{2}-\frac{1}{3}} + a\lg\left(2-\frac{3p}{2}\right) + 1 < \frac{a\lg\left(2-\frac{3p}{2}\right)+1}{2} < 0.$$

Therefore,

$$\delta\lg\left[\frac{p}{\frac{p}{2}-\frac{1}{3}}\right] + a\lg\left(2-\frac{3p}{2}\right) < -1.$$

This completes the proof.

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