Fortifying Barrier-coverage of Wireless Sensor Network with Mobile Sensor Nodes*

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Abstract. Recently, the barrier-coverage of wireless sensor network received huge attention thanks to the important applications such as border protection. In practice, sensor nodes are subject to intermittent failure to detect objects within its sensing range due to many reasons. Therefore, a barrier of sensor nodes may exhibit temporal loopholes. In this paper, we investigate the potential of mobile sensor nodes such as unmanned aerial vehicles and human patrols to fortify the barrier-coverage of static wireless sensors. We use a single variable first-order grey model, GM(1,1), based on the intruder detection history from the sensor nodes to determine which parts of the barrier is more vulnerable. Then, we relocate the available mobile sensor nodes to the identified vulnerable parts of the barrier in a timely manner. We show this relocation strategy is optimal in theory. By the simulations, we also evaluate the average performance of our algorithm.

1 Introduction

In the literature, the *coverage* of a *wireless sensor network (WSN)* refers to the quality of the sensor network satisfying a certain surveillance requirement. We

* This paper was jointly supported by National Natural Science Foundation of China under grant 91124001, the Fundamental Research Funds for the Central Universities, and the Research Funds of Renmin University of China 10XNJ032. This work was supported in part by US National Science Foundation (NSF) CREST No. HRD-1345219.

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say a WSN offers barrier-coverage over an area if the WSN guarantees to detect any object moving into the area. The barrier-coverage model has a wide range of important real-life applications such as border protection and enemy intrusion detection during a war. In practice, sensor nodes intermittently suffer from failures due to many reasons such as inaccurate readings and environmental changes. As a result, a barrier of wireless sensors has a chance to exhibit loopholes which allow some intruder to pass the barrier without being detected. Unfortunately, in many applications scenarios of barrier-coverage of wireless sensor networks such as enemy intrusion detection in the battlefield, the intruders are intelligent enough to identify such loopholes. Once an intruder identifies a path to penetrate successfully (possibly detected, but not captured), it is likely that the other intruders will try the similar path in the near future. Therefore, in those applications, it becomes very crucial to identify such a trend and accordingly fortify the border security in a timely manner.

In this paper, we assume there is a WSN offering barrier-coverage over an area of interest. In detail, we follow the previous work such as [2, 3] and consider a belt area over which the barrier of sensors is deployed. This is because (a) the belt shape area is easier to handle and (b) a barrier coverage model which is successfully working in the belt area is also applicable to the regions with different shapes such as a ring. We further assume that each sensor node suffers from intermittent failures, whose pattern are not known. However, we can acccess the statistics of the intruders (fortunately) detected by each sensor node. Under the circumstance, we study how to relocate a set of available mobile sensor nodes (which are much more reliable and physically superior than the cheap ground sensors) to fortify the barrier of sensor nodes against the intruders which may alter their main routes for penetration. Largely, the contribution of this paper has two folds.

(a) Based on the previous history of the arrival time of intruders detected by each sensor node, we predict the likelihood of intruders being detected by each sensor node in the near future. For this purpose, we adopt a mathematical model known as a single variable first-order grey model, GM(1,1), which has been widely used to predict events which are repeatedly occurring and is known to be highly reliable and efficient for this purpose [4–8].
(b) Once we identify static sensor nodes which have higher chance to detect intruders, we relocate the available mobile sensor nodes nearby the static

sensors so that the area covered by these nodes can be monitored even more thoroughly. Since this should be done in a timely manner, it is necessary to relocate the mobile nodes in a way that the maximum travel distance among the nodes is minimized (i.e. all nodes move concurrently and we would like to minimize the delay to perform the relocation of all nodes). We introduce a new mobile sensor nodes relocation algorithm which tries to satisfy this requirement in a way that a static sensor node with higher chance to detect an intruder will obtain assist from more number of mobile sensor nodes. We also prove our relocation strategy is optimal.

We would like to emphasize that the main contribution of our work is to investigate how to utilize a given set of mobile sensor nodes to fortify the barrier-coverage of static sensors which can be intermittently faulty. We recognize the consideration of the other traditional quality factors of static sensor network such as energy-efficiency is still important in this model. But, we leave how to integrate those mechanisms to improve performance of this hybrid sensor network system as the future work. The rest of this paper is organized as follows. Section 2 introduce some preliminaries. In Section 3, we introduce a new two-phase algorithm to identify the static sensor nodes to be fortified and to relocate the mobile sensor nodes accordingly. We present the simulation results and make discussions in Section 4. Finally, we conclude the paper in Section 5.

2 Preliminaries and Problem Statement

2.1 Network Model

A barrier coverage model which is successfully working in the belt area is also applicable to the regions with different shapes such as a ring [2, 3]. Therefore, this paper considers a WSN of n static sensor nodes within a two-dimensional rectangular area along with m mobile sensor nodes with limited sensing capability. Throughout this paper, we assume the intruders are moving from the top of the area (outer space) to the bottom (inner space) to trespass, but never circumvent the area (i.e. we are considering a rectangular area whose rightmost side is adjacent to the leftmost side). The static sensor nodes are deployed in the area and already providing barrier-coverage over the bottom region of the area. However, each sensor node suffers from temporal failure due to some reasons and the barrier may exhibit some loopholes. To minimize the loopholes, the mobile sensor nodes are (initially randomly) deployed in the area and will relocate themselves to enhance the quality of the coverage. We follow Saipulla et al. [9] and assume the coordinate (x, y) of each sensor node is known in advance, which can be done using either an on-board GPS unit or any existing localization mechanism. We further assume that the mobile sensor nodes have the knowledge of their locations within the area. Each sensor node has a sensing range r and is capable of detecting any intruder within its sensing region, whose shape resembles a disk with radius r centered at the sensor node. We say an intruder is covered or detected by a static sensor node or a mobile node once the intruder moves into the sensing region of the node [10].

2.2 Single Variable First-order Grey Model, GM(1,1)

This section introduces GM(1,1) which can be used predict the time that the next intruder will arrive at a sensor node based on the history of intruders collected by the sensor node. Suppose we have an initial intruder arrival time sequence measured by the sensor node,

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(l)\}, \tag{1}$$

where $x^{(0)}(i)$ is the time series data at time i and l is an integer such that $l \geq 4$. Based on the initial time series, we generate a new time-series

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(l)\}, \tag{2}$$

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$ for $k = 1, 2, \cdots, l$. The reason to accumulate the measures is to (a) provide the middle message of building a model and (b) weaken the variation tendency [4]. Then, we need to solve the following first-order differential equation of grey model GM(1,1):

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{3}$$

by determining a and b. Here, the (a, b) pair satisfying the equation can be computed by least squares, i.e.

$$(a, b)^T = [\mathbf{X}^T\mathbf{X}]^{-1}[\mathbf{X}^T\mathbf{Y}], \text{ where} \tag{4}$$

$$\mathbf{X} = \begin{pmatrix} -\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2)] & 1 \\ -\frac{1}{2}[x^{(1)}(2) + x^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}[x^{(1)}(n-1) + x^{(1)}(n)] & 1 \end{pmatrix}, \mathbf{Y} = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix}$$

Once we obtain the (a, b) pair, we plug them into the differential equation in Eq. (3) and solve it to obtain a GM(1,1) forecast model as follow:

$$\hat{x}^{(1)}(k+1) = [x^{(0)}(1) - \frac{b}{a}]e^{-ak} + \frac{b}{a}, \tag{5}$$

for $k = 1, 2, \cdots, n$. Here, $\hat{x}^{(1)}(k+1)$ is the predicted value of $x^{(1)}(k+1)$ at the time slot $k+1$. From this equation, we can obtain the *forecast value* of $\hat{x}^{(0)}(k+1)$ at time $k+1$ as a function of $\hat{x}^{(1)}(k+1)$ and $\hat{x}^{(1)}(k)$, which is

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k). \tag{6}$$

In the literature, this model is also referred as "Whole Data GM(1,1) Model". Note that as we can see from the equations above, its forecast data series is solely dependent on the historical data collected.

2.3 Problem Statement and Our Approach

In this paper, we study how to fortify the barrier of sensors using mobile sensor nodes. In our problem, the intruders are intelligent to detect a part of the sensor barrier which suffers from temporal failure more frequently. Therefore, we assume that a sensor node which fortunately detects larger number of intruders is more likely to be vulnerable. Based on this observation, we measure the vulnerability of each sensor node using GM(1,1) whose only input is the history of intruders collected by the sensor node, and it outputs which sensor node has a better chance to detect intruders in the near future, and thus more vulnerable. Once a set of vulnerable sensor nodes are identified, we relocate the available mobile sensor nodes to assist the vulnerable static sensor nodes such that the maximum travel distance of the mobile sensor nodes is minimized. As a result, this relocated can be achieved in a timely manner.

3 Predict and Fortify: A New Way to Improve Barrier-coverage using Mobile Sensor Nodes

In this section, we introduce our two-phase algorithm to dispatch available mobile sensor nodes in a timely manner so that the weak part of the barrier of sensors can be effectively fortified. Let X be the random variable of the number of intruders detected by a barrier of sensors during a certain time period.

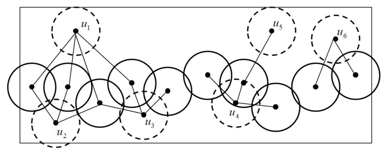
Clearly, this inter arrival time of intruders can be modeled as a renew process. We use Poisson distribution with parameter $\lambda > 0$ as the probability distribution of the number of intruders since this distribution has been widely adopted to model such a real world random event. Note that the expected value of a Poisson random variable X with parameter λ is λ, i.e. $\lambda = E(X)$.

3.1 Predicting Vulnerability of Static Sensors

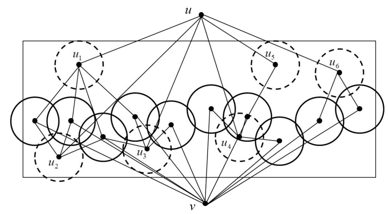
Let T_i^k be the time of k_{th} intruder detected by a static sensor node s_i. As we introduced, to apply GM(1,1), we assume that T_i^k is available for any $1 \leq k \leq l$ and $1 \leq i \leq n$ pair, where $l \geq 4$ is the number of intruders detected so far and n is the number of static sensor nodes. Then, using GM(1,1), we obtain $\hat{T}_i^{k+1}$, which is the predicted time that $k+1_{th}$ intruder (or the first intruder in the next time slot) will arrive at s_i for each i. Then, we compute $\Delta_i = \hat{T}_i^{k+1} - T_i^k$, which is the expected inter arrival time of $k+1_{th}$ intruder. Then, we define we compute the weight of s_i as $W_i = \frac{\lambda}{\Delta_i}$. This equation implies that with larger expected inter arrival time Δ_i, s_i will detect less number of intruders in the next time slot. Therefore, we can determine that a sensor node s_i with higher W_i value is more vulnerable. Let F_i be the number of mobile sensors needed by sensor node s_i. Clearly, the more W_i is, the higher F_i should be. One good equation that we can use is $F_i = |\lceil \frac{W_i}{\alpha} \rceil - c|$, where α is used to normalize W_i so that $\sum_{\forall i} F_i$ cannot exceed m, the total number of available mobile sensor nodes, and c is introduced to distinguish the group of vulnerable sensors from the rest. For the sake of simplicity, we set $\alpha = 1$, $c = 1$, and proceed.

3.2 Strengthening Barrier with Mobile Sensors

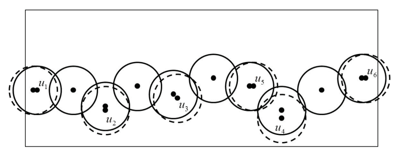
Suppose $\mathcal{V}$ be the set of vulnerable sensor nodes, i.e. $\mathcal{V} = \{s_i | F_i \geq 0\}$, identified by the previous phase. Then, for each sensor node s_i, we would like to (ideally) move at most F_i mobile sensor nodes to assist s_i. Note that we normalized $\alpha = 1$ and $c = 1$, and thus $\sum_{\forall i} F_i \geq m$ may happen. However, our strategy for relocating mobile sensor nodes introduced in this section is a best effort one, and thus it still works. In this section, we assume each mobile node is allowed to move at most $\mathcal{D}$ unit distance through the three steps introduced below. In the following section, we will explain how optimal $\mathcal{D}$ can be found.



(a) Step 1: there is a line between a mobile node u_i to a static sensor node if their Euclidean distance is no greater than a limitation, say $\mathcal{D}$.



(b) Step 2: two nodes u and v are added, and a bipartite graph is constructed. Then, a max-flow algorithm is applied to find the maximum flow from u to v.



(c) Step 3: the mobile nodes are relocated onto the static sensor nodes. This happens only if the max-flow value is equal to the number of mobile nodes. Otherwise, Step 1 and Step 2 are repeated after $\mathcal{D}$ is adjusted properly.

Fig. 1. This figure illustrates how mobiles nodes are assigned.

– Step 1: Suppose $S = \{s_1, \cdots, s_q\}$ is the set of sensor nodes identified to be vulnerable in the previous phase. From S, we first induce S' such that for each $s_i \in S$, we add $s_{(1,1)}, s_{(1,2)}, \cdots, s_{(1,F_i)}$ to S'. Let $M = \{u_1, u_2, \cdots, u_m\}$ be the set of mobile sensor nodes available. Next, we construct the bipartite graph $\mathcal{B} = \{S', M, E\}$, where E will contain an edge between $s_{(a,b)} \in S$ and $u_j \in M$ only if s_a is reachable from u_j if their Euclidean distance is at most $\mathcal{D}$.
– Step 2: From $\mathcal{B} = \{S', M, E\}$, we construct a new graph $\mathcal{G} = (V_G, E_G)$ such that $V_G = S' \bigcup M \bigcup \{u, v\}$ and $E_G = E \bigcup \{(u, s_{(i,j)}| \text{ for all } s_{(i,j)} \in S'\} \bigcup \{(v, u_i)| \text{ for all } u_i \in M\}$. Here we assume the capacity of each edge is 1. Then, we apply a maximum flow algorithm such as Ford-Fulkerson[11]) over $\mathcal{G}$.

– Step 3: Finally, the mobile sensor nodes are assigned in a way that if the maximum flow includes an edge from $s_{(i,j)} \in S'$ to $y \in M$, we assign the mobile sensor node y to s_i. Fig. 1 illustrates how the three steps work.

3.3 Computation of Optimal $\mathcal{D}$

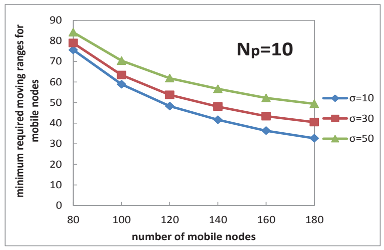
To find the optimal $\mathcal{D}$, we utilize binary search. We first compute the distance between every static sensor node and mobile node pair. Suppose $\{\mathcal{D}_1, \mathcal{D}_2, \cdots, \mathcal{D}_q\}$ be the list of distinct distances sorted by non-decreasing order. Then, we initially set $\mathcal{D} \leftarrow \mathcal{D}_{\lceil q/2 \rceil}$ and apply our two-phase algorithm introduced in the previous two steps. If there exists a mobile node m which is not assigned, then we increase $\mathcal{D}$ by setting $\mathcal{D} \leftarrow \mathcal{D}_{\lceil (q+q/2)/2 \rceil}$. Otherwise, we decrease $\mathcal{D}$ by setting $\mathcal{D} \leftarrow \mathcal{D}_{\lceil (1+q/2)/2 \rceil}$. We keep repeat this until we cannot proceed any further. Then, we will find minimum $\mathcal{B}$ which allows all of the mobile sensor nodes to be assigned. We now prove this strategy results in an optimal solution for this relocation problem.

Theorem 1. *The proposed relocation algorithm with binary search results in an optimal solution.*

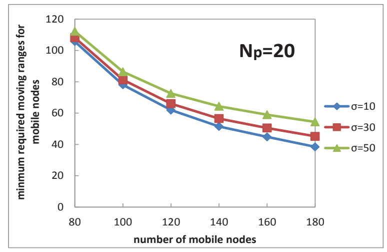
Proof. The proof of Lemma 1 is omitted due to space limitation.

3.4 Further Extension with Time Slots

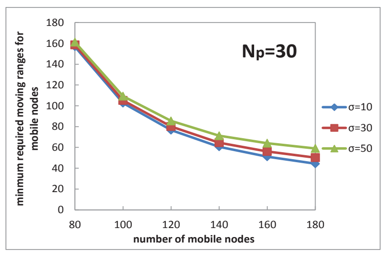
The algorithm described above can be easily implemented in a time slot based system as done by He et al. [1]. That is, we first consider the continuous time domain into a series of time slots with the same length. Then, we assume the time series shown in Eq. (1) are from current time slot. Then, using the first phase of our approach described in this section, we determine the vulnerability of each sensor node in the next time slot. Once decided, we deploy the mobile sensor nodes using the second phase of our approach. At the end of each time slot, we reanalyze the vulnerability of each sensor node and redistribute the sensor node. One benefit of this time slot based approach against the case without it is that we use relatively new history of intruders only rather than using all of the accumulated history to analyze the vulnerability of each node. Depending on the applications, this can improve the accuracy of the prediction achieved by grey model GM(1,1).



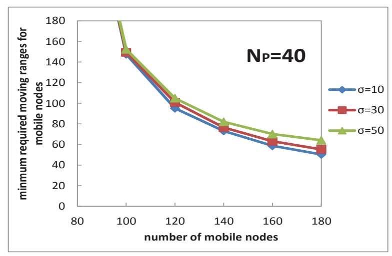
(a) Minimum required moving range for $N_p = 10$



(b) Minimum required moving range for $N_p = 20$



(c) Minimum required moving range for $N_p = 30$



(d) Minimum required moving range for $N_p = 40$

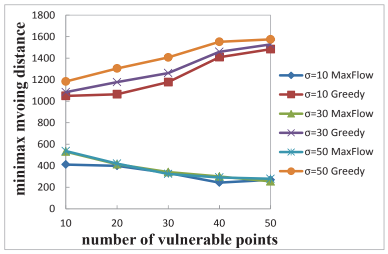
Fig. 2. Performance evaluation of the second phase of the proposed algorithm.

4 Simulation Results and Analysis

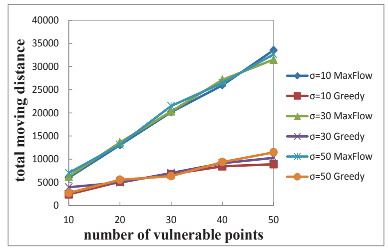
4.1 Performance Evaluation of Mobile Node Relocation Algorithm

In this section, we evaluate the performance of the second phase of our algorithm. We set the number of vulnerable sensor nodes N_p to be 10, 20, 30, and 40. In this simulation, we consider a barrier formed by 100 sensors deployed over a 2000×200 rectangle space. Then, we randomly deploy m mobile sensor nodes along the barriers based on three different random offset variances σ=10, 30, and 50. Note that with larger variance used, the mobile sensors have a better chance to be located further from the barrier. Under the same parameter setting, we apply our algorithm for 100 instances and compute the averaged value.

Fig. 2 shows the relationship among the number of mobile nodes, the minimum required moving distance of the nodes, and N_p. In Fig. 2(a), N_p is set to 10 and the number of mobile nodes is increased. As we can observe, with more mobile nodes, the mobile node can be completely relocated within less time. We can also observe that with smaller σ value, the travel distance becomes smaller.



(a) Minimum moving range to monitor all vulnerable points



(b) Total moving range to monitor all vulnerable points

Fig. 3. Performance evaluation of mobile node relocation algorithm compare with He et al.'s strategy.

We can observe the similar trend from Fig. 2(b), Fig. 2(c), and Fig. 2(d). By comparing Fig. 2(a), Fig. 2(b), Fig. 2(c), and Fig. 2(d), we also can learn the effect of σ is constant regardless from the N_p value, which seems natural. On the other hand, with large N_p value, the maximum travel length of mobile sensor nodes for relocation is greater. From this result, to cover all of the vulnerable nodes, a mobile node may need to travel further as the number of vulnerable nodes increase. We believe this is because to assign all of the mobiles nodes, some nodes may need to travel very far, and this happens more often if we have more number of vulnerable nodes.

4.2 Performance Comparison of Mobile Node Relocation Algorithm Against He et al.'s Strategy [1] for Our Purpose

In [1], He et al. introduced a multiple mobile sensor node relocation algorithm called CSP whose goal is to relocate a group of mobile sensor nodes into a subset of regions based on some probability model to maximize the chance to detect intruders. Therefore, their algorithm also can be used to relocate mobile sensor nodes to solve our problem by replacing our max-flow based algorithm after Step 2 of Phase 2 described in Section 3.2. Note that our algorithm also can be used for their problem. In detail, the CSP algorithm is a greedy algorithm which tries to assign each available mobile sensor to the closest vulnerable point. It assumes that all mobile sensors and vulnerable points are on a straight line, and each vulnerable point is monitored by one mobile sensor. In our scenario, our mobile sensors and vulnerable points are not necessarily on a straight line. However, we can still use the main idea of CSP algorithm. This can be done by iteratively selecting a vulnerable point that has not been assigned any mobile sensor yet, and assign it to the closest available mobile sensor. This process is repeated until all vulnerable points are occupied. Since CSP algorithm assumes the number of avail mobile sensor nodes is equal to the number of vulnerable points, so we keep this assumption for a fair comparison.

Fig. 3 show our simulation results. From the figures, we can learn that the min-max distance of the outputs of our algorithm is better than that of He et al's greedy algorithm (greedy).On the other hand, the total distance that the mobile sensor nodes are moving around is larger than that of greedy's.This is due to the difference in the objectives of the algorithms. That is, the goal of our algorithm is to minimize the min-max distance achieved by the mobile sensor nodes while the goal of He et al's greedy algorithm is to minimize the total (average) distance achieved by the mobile sensor nodes. Therefore, our algorithm outperforms He et al's greedy algorithm for our problem.

5 Conclusion

In this paper, we introduce a new paradigm to use mobile sensors to fortify the barrier of static wireless sensors. Our approach is based on GM(1,1) which helps to predict which sensor node has a better chance to detect intruders based on the past record of the intruders detected. We assume that a sensor node has a higher chance to detect an intruder because the intruder consider the area covered by the sensor node is easier to penetrate. Therefore, we deploy available mobile sensor nodes to strengthen the coverage of those sensors. The algorithm that we proposed in this paper also utilizes a binary search approach to minimize the maximum travel length of the mobile sensor nodes, and thus make the relocated done in a timely manner. Our simulation results suggest some interesting properties of our algorithm, especially about the second phase which concern about the relocation.

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