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Fisher Information of Mine Collapse Hole Detection Based on Sensor Nodes Connectivity

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Abstract: It is very important to detect a collapse hole for coal mine workers. The possibility of detecting the collapse hole using WSN is presented, because the tunnel in coal mine is narrow and the poor working condition. Comparing three types of the hole detection methods, it is seen that the connectivity based methods are used to detect coal mine collapse better than other methods. By establishing a 2-D model of the collapse hole in coal mine, a class of algorithms for detecting the collapse hole in coal mine is described. Based on log-normal shadowing channel model, the accuracy of detecting the collapse hole in coal mine using Fisher Information is analyzed. Numerical calculation shows that connectivity based localization schemes are used to detect collapse hole of coal mine better. *Copyright © 2013 IFSA.*

Keywords: Fisher information, Collapse, Hole detection, Mine, Underground.

1. Introduction

Coal mine collapse is one of the main reasons result in coal mine fatalities in the past 10 years in the world [1]. Hence, it is very important to detect a collapse hole and accurately provide location references for coal mine workers. Since the coal mine collapse may destroy some coal safety monitoring devices, detecting the collapse hole in coal mine becomes a great challenge. The utilization of wire sensors to monitor coal mine is the primary methods at present. However, the wired method makes the monitoring systems less scalable and vulnerable because of the poor working conditions in a tunnel of coal mine. Once coal mine collapse occurs, all wired sensors may be destroyed, and it is impossible to detect the collapse hole.

Wireless sensor network (WSN) is an event based self-organized wireless network that relies on deploying spatially dense sensor nodes observing a physical phenomenon [2-5]. Compared with traditional wire sensing, WSN can achieve larger coverage area, greater accuracy, and more flexible deployment. The utilization of a WSN to monitor coal mine is benefit. Once coal mine collapse occurs, not all sensor nodes of a WSN are destroyed. So, it is possible to detect the collapse hole in coal mine collapse hole. For example, Li and Liu present a method based on a regular beacon strategy to detect the collapse hole in coal mine by regulating a mesh sensor network deployment [1].

When a collapse occurs, the group of destroyed sensor nodes in the coal mine wireless sensor network creates a hole [6]. The collapse hole boundary separates all the faulty sensor nodes from the working nodes. Generally, there can be three types of the hole detection methods. The approaches based on geometric location methods [7, 8] rely on the nodes having geographical locations, and can find more accurate boundary nodes than other two methods, but each node has to equip extra device such as GPS to obtain the geographical locations. Unlike the methods, the statistical methods [9, 10] without having location information usually assume the sensor nodes are uniformly distributed on the sensing field. The major weakness of the statistical methods is that the criteria for detecting hole acquires from the statistical characteristics cannot guarantee to find hole precisely. The connectivity based methods [6, 11, 12] use the information of neighboring sensor nodes connectivity to detect the hole. Normally, the method has higher packet control overheard than previous two methods due to having to collect information from neighboring sensor nodes; however, it does not need location information and has better accuracy of finding boundary nodes than statistical method. The sensor nodes neither can be equipped any additional devices such as GPS, nor are uniformly distributed because of the narrow tunnel and the poor working conditions in the tunnel in coal mine. So, the connectivity based methods are used to detect coal mine collapse better.

Connectivity is just a binary variable determined by whether or not a sensor node can demodulate and decode a packet transmitted by another sensor node. Connectivity measurements can be obtained by comparing the Received Signal Strength (RSS) value between the two nodes against a power threshold. The RSS can be used to implement range-based localization [13]. The localization methods are popular because no additional hardware is required on the sensor nodes. However, the range estimates using RSS are inaccurate and can lead to large localization error, because the RSS value is affected by unpredictable shadowing and fading in the tunnel in coal mine. Yet connectivity is the binary variable carrying information regarding sensor nodes location, and is often discussed without considering that it is affected by shadowing and fading channel. So, the connectivity based methods for localization have been actively researched in hole detection and ad hoc routing in WSN [14-16].

Connectivity measurements are actually just a binary quantization of the RSS measurements against a power threshold. Because RSS measurements are affected by unpredictable shadowing and fading in the tunnel in coal mine, it is very important to analyze accuracy of detecting the coal mine collapse hole using the connectivity based methods. The rest of this paper is organized as follows. Section 2 discusses the system models including 2-D model of the coal mine collapse hole and a class of algorithms for detecting the coal mine collapse hole using the connectivity based methods. Section 3 analyzes the accuracy of detecting collapse hole using Fisher Information. Section 4 describes numerical calculation and discussion. Section 5 concludes this paper.

2. System Model

2.1. 2-D Model of Coal Mine Collapse Hole

Generally, the tunnel of coal mine can be classified as arch-shaped, rectangle, trapezium, and semicircle tunnel. For convenience, we consider rectangle tunnel in this paper. A cluster of sensor nodes are deployed on the walls and roofs of the tunnel, as shown in Fig. 1 (a). To facilitate collapse hole detection, Fig. 1 (a) can be unfolded a 2-D representation as depicted in Fig. 1 (b).

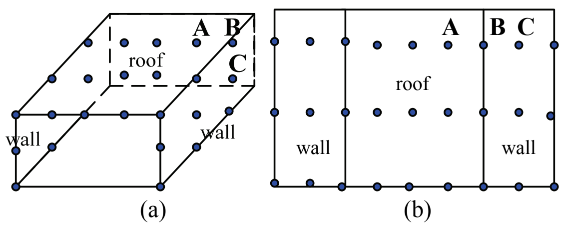

Fig. 1. A cluster of sensor nodes deployment.

In Fig. 1, the relationships between the neighboring sensor nodes in Fig. 1 (b) are the same as in Fig. 1 (a). However, the distance between any two nodes in Fig. 1 (b) is greater than or equal to the distance between the pair in Fig. 1 (a). Thus, the real connectivity of the WSN is no less than shown in the 2-D representation in Fig. 1 (b), and the accuracy of the collapse holes detection in Fig. 1 (b) is preserved in Fig. 1 (a).

So, a cluster of sensor nodes are modeled as a 2-D graph, $G = (V, E)$, where each vertex represents a sensor node, V is the set of a cluster sensor nodes, and two vertices are connected by an edge in E if and only if their distance is at most the guaranteed communication radius. Once a mine collapse occurs, some sensor nodes n_1, n_2, …, $n_k \in V$ are destroyed. The extent of these damaged nodes creates a collapse hole with convex hulls, which is surrounded by alive sensor nodes that contain all the damaged sensor nodes in Fig. 2.

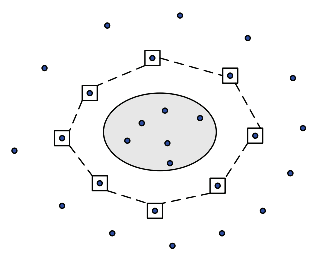

Fig. 2. A collapse hole created by damaged sensor nodes.

2.2. Algorithm for Detecting Collapse Hole Using Connectivity

Connectivity simple report whether or not a sensor node can demodulate and decode a packet transmitted by another sensor node. Connectivity measurements can be obtained by comparing the Received Signal Strength (RSS) value between the two nodes against a power threshold. Because the RSS measurements are affected by unpredictable shadowing and fading in the tunnel in coal mine, the connectivity can be described by a random binary variable Q_{ij} :

$$Q_{i,} = \begin{cases} 1, & P_{ij} \geq P_{th} \\ 0, & P_{ij} < P_{th} \end{cases} \tag{1}$$

where P_{ij} is the RSS measurement received at sensor node i transmitted by sensor node j, P_{th} is the power threshold of sensor node. Eq. (1) shows that sensor node i can demodulate and decode a packet transmitted by sensor node j if $P_{ij} \geq P_{th}$, and $Q_{ij} = 1$; sensor node i can not demodulate and decode a packet transmitted by sensor node j if $P_{ij} < P_{th}$, and $Q_{ij} = 0$.

The connectivity based methods will use the assumption that two sensor nodes are "connected" if $Q_{ij} = 1$, and "disconnected" if $Q_{ij} = 0$. The advantage of these methods is that location can be discussed without knowing the propagation model's parameters. So, a class of algorithms for detecting the collapse hole in coal mine can be described as follows [1, 17]:

Step 1 (initialization): Each sensor node broadcasts a ping requesting information to neighboring sensor nodes. If $P_{ij} \geq P_{th}$, sensor nodes rely with their ID, and the pinging node can create a list of its neighboring sensor nodes.

Step 2 (integrity checking): If a coal mine collapse occurs, each sensor node pings its neighboring sensor nodes, keeps track of the responses and compares the list of neighboring sensor nodes. If $P_{ij} \geq P_{th}$, sensor node receives the ID (Identification Number) of sensor node j , and marks sensor node j as alive. If $P_{ij} < P_{th}$, sensor node i can not receive ID of sensor node j, and marks the sensor node as missed. If the node's number of missed neighboring nodes exceeds a threshold, sensor node i marks itself as belonging to the collapse perimeter.

Step 3 (collapse hole scanning): According to the list of sensor nodes marked as "on the collapse perimeter", the classical Graham algorithm [18] is used to detect the collapse hole with convex hulls.

3. Accuracy of Detecting Collapse Hole

As shown in Section 2, analyzing the accuracy of detecting collapse hole using connectivity is to analyze the accuracy of estimating distance d between neighboring sensor nodes equivalently using Q_{ij} . So, we consider the topic of estimate distance d between neighboring sensor nodes from connectivity measurements using Fisher Information.

3.1. Channel Model

Because the tunnel is narrow and poor environment in coal mine, the RSS is attenuated by path losses, fading and shadowing losses [19]. Path loss is the deterministic reduction function of distance d between neighboring sensor nodes. Fading is the effect of multipath propagation. Because many wireless sensor nodes use spread-spectrum techniques, the fading can be reduced mostly and its impact on the attenuated RSS is not significant. Shadowing is the loss incurred as a signal passes through permanent obstructions (e.g. walls, buildings). For mostly sensor nodes in the tunnel, shadowing losses can not be countered. When a collapse occurs, shadowing losses are greater. So, the RSS values follow the log-normal shadowing model, a channel model widely used in WSN [20], [21].

Let $P_r(0)$ is the received signal power at sensor node with the reference distance d_0 (Typically $d_0 = 1$), and γ is the path loss exponent, a parameter that depends on the environment where communication occurs (typical values are 2 and 4 [22]). Under log-normal shadowing model, the received power when the two sensor nodes are at a distance d can be written as:

$$\ln P_r(d) = \ln P_r(0) - \gamma \ln d + w \,, \tag{2}$$

where w is the zero-mean random variable with normal distribution $N(0, \sigma^2)$.

3.2. Fisher Information

In this paper, we focus on estimating distance d between neighboring sensor nodes from connectivity measurements, which carry information regarding sensor nodes location. As is well known, the Fisher Information measures the amount of information that a random variable carries about an unknown parameter. And the inverse of the Fisher Information, known as the Cramer-Rao Bound, is the minimum variance for any unbiased estimator. Here, the random variable Q_{ij} defined by Eq. (1) is used to estimate d. So, $Var\{\hat{d}\}$, the variance of estimating d is:

$$Var\{\hat{d}\} \geq 1/I(d), \quad (3)$$

where $I(d)$ is the Fisher Information of estimating distance d using the random variable Q_{ij}.

3.2.1. Fisher Information of RSS Measurements

For notational convenience, we define $\alpha = 2/\gamma$, $z = \left(P_r(0)/P_r(d)\right)^{\alpha}$. Then Eq. (2) can be written as:

$$z = d^2 e^{-\alpha w} \quad (4)$$

So, the underlying estimation problem is to estimate d from the RSS measurements z satisfying Eq. (5), given the knowledge of α and σ^2.

Taking the logarithm of Eq. (5), we obtain

$$\ln z = 2\ln d - \alpha w \quad (5)$$

Let $l = \ln z$, l is a random variable with normal distribution $N\left(2\ln d, \alpha^2\sigma^2\right)$. The log-likelihood functions given by

$$\ln\left[p(l,y)\right] = -\ln\left[2\pi\alpha^2\sigma^2\right] - (l - 2\ln d)^2 / 2\alpha^2\sigma^2 \quad (6)$$

Hence, the Fisher Information of RSS measurements is given by

$$I_{RSS}(d) = E\left[\left(\partial \ln\left[p(l,y)\right]/\partial d\right)^2\right] = k^2/d^2, \quad (7)$$

where $k = \gamma/\sigma$.

3.2.2. Fisher Information of Connectivity Measurements

As shown in Section 3, the underlying estimation problem is to estimate d from the connectivity measurements. Then the Fisher Information of connectivity measurements depend not only the d between neighboring sensor nodes, but also the value of the power threshold P_{th} in Eq. (1). For convenience, P_{th} need to be converted into the distance threshold d_{th}. From Eq. (4), it can be observed that l has a non-affine dependence on d and an affine dependence on w. Hence, no efficient estimator exists for this problem [23]. This leads us to choice the Maximum Likelihood Estimator (MLE) $\hat{d}_{th}$ of the distance threshold d_{th}. The $\hat{d}_{th}$ is given by

$$\hat{d}_{th} = \underset{d}{\overset{P_r(d)=P_{th}}{\arg\max}} \ln\left[p(l,y)\right] = \left(P_r(0)/P_{th}\right)^{1/\gamma} \quad (8)$$

From [24], consider the case of 2-level quantized RSS. The Fisher Information of connectivity measurements is given by

$$I_{CON}(d.d_{th}) = k^2 h_r(d, d_{th})/d^2, \quad (9)$$

where the term $h_r(d, d_{th})$ depends on the ration between d and d_{th}:

$$h_r(d, d_{th}) = \frac{2}{\pi} \frac{\exp\left[-k^2 \ln(d/d_{th})^2\right]}{1 - erf\left[k \ln(d/d_{th})/\sqrt{2}\right]^2}, \quad (10)$$

where $erf(\cdot)$ is the error function.

4. Numerical Calculation and Discussion

4.1. Numerical Calculation

In this subsection, we investigate the Fisher Information $I_{RSS}(d)$ and $I_{CON}(d, d_{th})$ using numerical calculation.

4.1.1. The Path Loss Exponent's Effects on $I_{RSS}(d)$

Fig. 3 shows that the $I_{RSS}(d)$ as a function of d for different γ values (γ =4, 3, 2.5) and fixed σ value ($\sigma = 2$). Fig. 3 describes that amount of the $I_{RSS}(d)$ available to estimate d decreases for increasing values of the distance d, and increase for increasing values of the γ values. This shows that the estimates become more accurate because the attenuation caused by the path loss clears the RSS measurement.

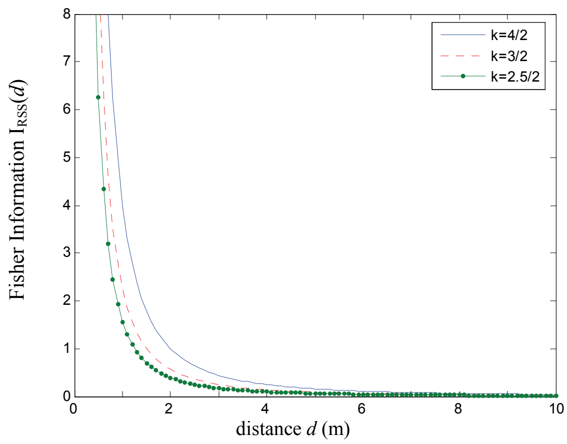

Fig. 3. Fisher Information for RSS measurements at σ=2 .

4.1.2. The σ Values' Effects on $I_{RSS}(d)$

Fig. 4 shows that the $I_{RSS}(d)$ as a function of d for different σ values (σ =2, 3, 4) and fixed γ value ($\gamma = 3$).Fig.4 describes that amount of $I_{RSS}(d)$ available to estimate d decreases for increasing values of the distance d and increasing values of the σ values. This shows that the estimates become less accurate because the variability caused by the RF shadowing blurs the RSS measurement.

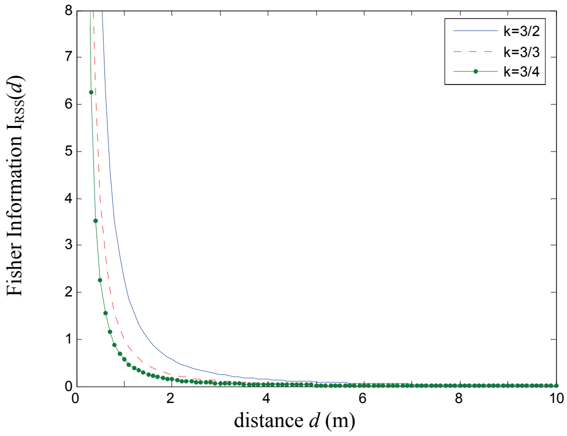

Fig. 4. Fisher Information for RSS measurements at γ=3 .

4.1.3. The k Values' Effects on the Fisher Information $I_{CON}(d, d_{th})$

Fig. 5 shows that the $I_{CON}(d, d_{th})$ as a function of d_{th} when d=5m for different k values (k=3/4, 3/3, 2/3), and Fig. 6 shows that the $I_{CON}(d, d_{th})$ as a function of d_{th} when k=4/2 for different d values (d=2, 3, 4).

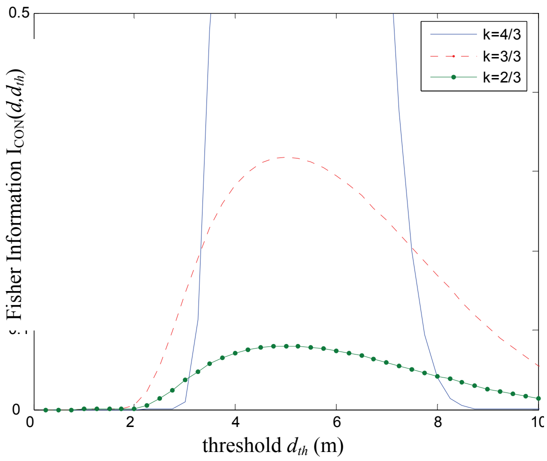

Fig. 5. Fisher Information for connectivity measurements at different k values.

Fig. 5 and Fig. 6 describe that the $I_{CON}(d, d_{th})$ always peaks when $d_{th} = d$. In other words, connectivity measurements reach the maximum information if the distance threshold equals to the true distance between neighboring sensor nodes. From Eq. (10), the maximum Fisher Information of connectivity measurements $I_{CON}(d, d_{th}) = 0.63 I_{RSS}(d)$ if $d_{th} = d$. So, $I_{CON}(d, d_{th})$ is always lower than $I_{RSS}(d)$.

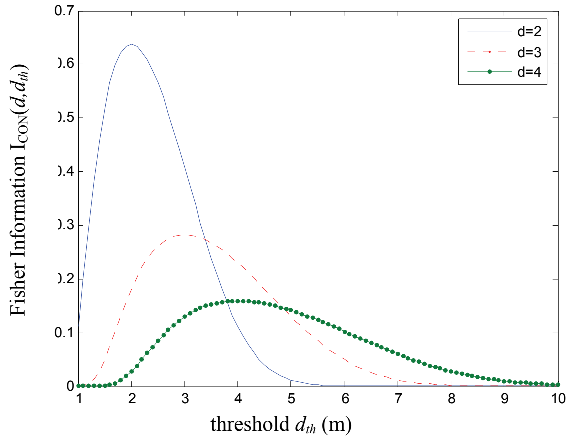

Fig. 6. Fisher Information for connectivity measurements at different d values.

4.2. Discussion about Accuracy of Detecting Collapse Hole

As shown in Section 4.1, RSS measurements carry greater Fisher Information than connectivity ones. However, this is only true as long as the neighboring sensor nodes are within the radio coverage of each other. When sensor nodes are within each other's radio coverage, they are able to communication and successfully exchange radio message.

Depending on the choice of P_{th} , two neighboring sensor nodes that are within each other's radio range can be considered connected or disconnected. When the neighboring sensor nodes are far from radio coverage, they will not be able to communication. So, no RSS information can be collected, and $I_{RSS}(d) = 0$. Instead, the sensor nodes far from radio coverage can be associated to the value Q_{ij} , and $I_{CON}(d, d_{th}) > 0$.

As shown above, RSS range-based localization schemes are more accurate when the neighboring sensor nodes are in the radio coverage of each other, but connectivity based localization schemes are is naturally suited to localize nodes that are far from radio coverage. Hence, connectivity based localization schemes are used to detect collapse hole of coal mine better.

5. Conclusions

It is very important to detect a collapse hole for coal mine workers. This paper presents the possibility of detecting the collapse hole using WSN, because the tunnel in coal mine is narrow and the poor working condition. Comparing three types of the hole detection methods, we think that the connectivity based methods are used to detect coal mine collapse better. By establishing a 2-D model of the collapse hole in coal mine, we describe a class of algorithms for detecting the collapse hole in coal mine. Based on log-normal shadowing channel model, we analyzes the accuracy of detecting the collapse hole in coal mine using Fisher Information, and make numerical calculation. Finally, we make the conclusion as follows:

- The larger the path loss exponent, the greater Fisher Information.
- The larger the variability caused by the RF shadowing, the less Fisher Information.
- When sensor nodes are within each other's radio coverage, the accuracy of detecting the collapse hole using RSS measurements is higher than connectivity ones; When the neighboring sensor nodes are far from radio coverage, no RSS information can be collected, and $I_{RSS}(d)=0$. Instead, the sensor nodes far from radio coverage can be associated to the value Q_{ij}, and $I_{CON}(d,d_{th})>0$. Hence, connectivity based localization schemes are used to detect collapse hole of coal mine better.

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