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3D space detection and coverage of wireless sensor network based on spatial correlation

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A B S T R A C T

With an increasing number of the WSN applications in 3D space such as in outer space, atmosphere or underwater, the 3D space signal detection and coverage problems become more and more important. However, the 2D assumption, such as the binary detection model, is still used in the research referred to the 3D circumstance to determine whether the event to be detected occurs or not, leading to major inaccuracies. This assumption maybe useful, but in most circumstances, where sensor nodes are distributed in 3D space, this is not the case because the signal intensity from the event we want to detect decreases while the distance from the sensor node increases. At the same time, the signal is interfered by the noise in 3D space. These factors make the sensor node hard to accurately detect the occurrence of the event due to “false alarm” or “missing alarm”, resulting in extra difficulties in 3D wireless sensor network coverage. Here we focus on detection issues by using probabilistic sensing model with five different collaborative detectors based on spatial correlation and signal detection theory. Based on the above analysis, we propose the 3D space detection and coverage growing algorithm, which uses probabilistic unit sensing model and four different polyhedrons, aims at achieving the seamless 3D space coverage while the number of nodes required for a fixed space is minimized. Results from simulations demonstrate that the sensing model with collaborative energy detector (ECD) achieves the widest sensing radius, which is 1.1 times of Collaborative CD; 1.48–1.62 times of Collaborative ED. Results also demonstrate that our algorithm could achieve the seamless 3D space coverage and truncated octahedron is the best to fill the determined space, resulting in the least nodes required.

1. Introduction

Nowadays, an increasing number of the WSN applications have been used in outer space, atmosphere or underwater (Nazrul Alam and Zygmunt, 2008; Akyildiz et al., 2005; Heidemann et al., 2006), where sensor nodes are distributed in 3D space. For example, weather forecasting becomes more accurate if the 3D wireless sensor networks are placed in atmosphere. The ships in the ocean require the nodes to be deployed in the different depths of the water, thus creating a 3D network to monitor their operating states (Jiejun et al., 2005). In these circumstances, the wireless sensor nodes often have a certain distance from the source event in the 3D space, and they also should determine whether the event occurs or not through detecting the signal from the event while the signal attenuates in the 3D space with noise. So how to build the wireless sensor networks with large sensing range and achieve a large coverage in 3D space becomes a problem that should be addressed (Oktyg et al., 2008; Xiao et al., 2010).

The goal of WSN in 3D space, perceiving the occurrence of the target event, is similar to the case of 2D space. There have been a number of researches on detection and coverage problems; some of them consider about environmental noise, signal decay, and introduce the probabilistic model followed by the signal propagation from a target to sensor nodes (Zoghi and Kahaei, 2009; Qiu and Skafidas, 2012; Ahmed and Kanhere, 2005). A new routing scheme that adopts the probabilistic model is proposed in Qiu and Skafidas (2012). Both the probabilistic model and the coverage issue on the node placement strategy in two-dimensional (2D) space are introduced in Ahmed and Kanhere (2005) and Ahmed (2005). However, all of them do not consider the 3D coverage and the effects of the spatial correlation among sensor nodes.

Michaelides et al. introduce the spatial correlation on the coverage problem in 2D sensor networks (Michaelides and

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Panayiotou, 2007, 2009, 2011). Results show that spatial correlation that exists among the measurements of sensor nodes densely deployed in the target area can be exploited to reduce the false alarm probability and increase the sensing range of the nodes (Berger et al., 2001; Mehmet et al., 2004). But they did not consider 3D coverage as well. The 100% sensing coverage and the node placement strategy in 3D space are discussed in Nazrul Alam and Zygmunt (2008), but the sensor model used in Nazrul Alam and Zygmunt (2008) is just the binary detection model which does not consider the environmental noise and the spatial correlation.

In this paper, our focus is to apply the spatial correlation among the measurements of sensor nodes to the research of the signal detection and sensing space coverage issues of WSN in 3D space. The wireless sensor technique can be used to collect and process the signal from the source event in the space. In the previous study, the binary detection model (Ahmed et al., 2005c) was used to determine whether the event in a certain spot occurs or not. But this assumption is impracticable. The signal intensity from the event decreases while the distance from the sensor node increases in the practical circumstance. At the same time, the signal is interfered by the noise in the space. These factors make the sensor node hard to accurately detect the occurrence of the event in the 3D space due to “false alarm” or “missing alarm”. In particular, we attempt to address two problems: (1) Which detector should be used on the nodes to make their sensing range wider? (2) What is the best way to deploy the nodes to achieve seamless coverage for a 3D space so that the number of nodes is minimized? Here we first focus on detection issues by using probabilistic sensing model with five different detectors based on spatial correlation and signal detection theory. Then we propose a novel algorithm called the 3D space detection and coverage growing algorithm to solve the second problem.

First, considering spatial correlation can enhance the detection performance of detectors, we choose different categories of collaborative detectors with spatial correlation to determine the occurrence of the target event, and these detectors include collaborative mean detector (MD), collaborative energy detector (ED), collaborative covariance detector (CD) and collaborative enhanced covariance detector (ECD) (Dajun, 2013). Combined with the Neyman–Pearson principle (N–P principle), each of these detectors is adopted on sensor nodes to detect the occurrence of an event, resulting in different detection probabilities. Then the probability sphere for each detector can be got by the Monte-Carlo method, and its surface is composed of the sampling points with the same detection probability, this sphere is named as unit sensing model, and its radius is the sensing range of nodes. Result from simulations can demonstrate that the unit sensing model with ECD can achieve the widest sensing radius, which is 1.1 times of Collaborative CD; 1.48–1.62 times of Collaborative ED; and almost 2.61 times of Collaborative MD.

In terms of the coverage growing algorithm, four different built-in polyhedrons of the unit sensing model, which include truncated octahedron, rhombic dodecahedron, hexagonal prism and cube, are adopted to complete the seamless 3D space coverage. In this algorithm, we first choose one polyhedron from above four. Then starting at the center of space, the chosen polyhedrons with the same shape are gradually filled into the space under node placement growing sub-algorithm. And the sensor nodes are placed into the geometric center of each polyhedron. At last, results demonstrate that truncated octahedron turns out to be the best choice with a volumetric quotient of 0.68329, which is better than all the other polyhedrons (Nazrul Alam and Zygmunt, 2008). The number of nodes required for the coverage of a fixed space is up to the sensing radius of unit sensing model. If the sensing radius is wider, the number of nodes is smaller. Results demonstrate that truncated octahedron is best to fill the determined space, resulting in the least nodes required for our algorithm.

The remainder of this paper is organized as follows. In Section 2, we introduce the sensing model with single node and pairs of sensor nodes, and the spatial correlation theory. In Section 3, we present the 3D space detection and coverage growing algorithm. In Section 4, we compare the sensing range of unit sensing model with different detectors, and also compare the coverage efficiency of our algorithm with different polyhedrons. In Section 5, we make the conclusion and the prospect for the future.

2. The spatial correlation and the sensing model

2.1. Basic sensing model

In WSN, sensing is a paramount important function. In the previous studies, the sensing coverage of a sensor node is assumed to follow the binary detection model. Specially, an event that occurs within the sensing radius of a sensor node is assumed to be detected with probability 1 while any event outside the unit circle is assumed not to be detected. However, this model is based on an impracticable assumption. In the practical situation, the signal intensity from the event source decreases while the distance from the sensor node increases, and the signal will also be interfered by the noise in the process of propagation (Michaelides and Panayiotou, 2007). So two cases may have occurred in this circumstance, one is that the sensor node judges the event has already occurred, while it actually does not happen, this case is called as “false alarm”. The other is that the event has occurred in the space, but the sensor node does not detect it, which is called as “missing alarm”. We assume that X is a random variance representing whether the event occurs or not. Two completing hypotheses are summarized as follows:

$$\begin{cases} \mathrm{H}_0 : X = 0 \\ \mathrm{H}_1 : X = 1 \end{cases}$$

where H_0 is referred to as the null hypothesis representing the event has not occurred yet and H_1 as the alternative hypothesis representing the event has already happened. Then $p(X;\mathrm{H}_0)$ and $p(X;\mathrm{H}_1)$ are the probability distribution function of the decision that the event occurred under H_0 and H_1 respectively. Thus, $P(\mathrm{H}_1;\mathrm{H}_0)$ is the probability of false alarm (P_F), $P(\mathrm{H}_0;\mathrm{H}_1)$ is the probability of missed detection (P_M), and $P(\mathrm{H}_1;\mathrm{H}_1)$ is the probability of missed detection (P_D).

With the N–P principle, we can see that it is not possible to reduce both $P(\mathrm{H}_1;\mathrm{H}_0)$ and $P(\mathrm{H}_0;\mathrm{H}_1)$ at the same time. A typical approach is to hold one error probability fixed while minimizing the other. Generally, we usually seek to minimize $P(\mathrm{H}_0;\mathrm{H}_1)$ or equivalently to maximize $1-P(\mathrm{H}_0;\mathrm{H}_1)$, the latter is just $P(\mathrm{H}_1;\mathrm{H}_1)$. In summary, given the constraint $P_F{=}P(\mathrm{H}_1;\mathrm{H}_0)$, we wish to maximize $P_D{=}P(\mathrm{H}_1;\mathrm{H}_1)$. The N–P principle is stated in the following expression (Steven et al., 2011):

To maximize PD for a given $P_F = \alpha$ decide H_1 if

$$L(X) = \frac{p(X;\mathrm{H}_1)}{p(X;\mathrm{H}_0)} > T_\gamma \tag{1}$$

where the threshold T_γ is found from

$$P_F = \int_{\{X:L(X) > T_\gamma\}} p(X;H_0)dx = \alpha \tag{2}$$

In the period of sensing, each observed test statistic Z_i of sensor node i is represented as follows:

$$Z_i = S_i + W_i \tag{3}$$