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Impacts of sensor node distributions on coverage in sensor networks

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ABSTRACT

Network coverage is an important Quality of Service (QoS) measurement for many sensor network applications. Many existing studies on network coverage are based on the knowledge of sensor node distributions in sensing fields, which are often represented by given probability distributions. In this paper, we study the impacts of sensor node distributions on network coverage. We first show the impacts on network coverage by adopting different sensor node distributions through both analytical and simulation studies. We observe that assumed different sensor location distributions may lead to significant differences in coverage estimation. Then, we adopt a distribution-free approach to study network coverage, in which no assumption of probability distribution of sensor node locations are needed. The proposed approach has yielded good estimations of network coverage. Though only network coverage is studied in this paper, we believe that this methodology can be generalized and extended to estimation of other sensor network performance metrics.

1. Introduction

Wireless sensor networks (WSNs) have a wide range of applications. Making use of mobile nodes carried by animals [26] or automobiles [38] or deterministically deployed sensor nodes in fixed locations [104], many trials have demonstrated the potential of WSNs. Continuous miniaturization of sensor nodes can lead to future WSN applications where a large number of battery-powered sensor nodes are randomly and densely deployed and the network is left unattended to perform monitoring, tracking, and reporting functions [2,110]. One fundamental issue related to those applications is *coverage*, which, in general, can be considered as a *quality of service* measurement of the WSNs [69]. The WSN coverage problems can be generally divided into three types: area coverage where the objective is to monitor an area or a region, point coverage where the objective is to monitor a set of points or targets, and barrier coverage where the objective is to minimize the probability of an undetected penetration through a barrier monitored by a WSN [15].

The coverage problems have been widely studied in conjunction with energy efficiency and lifetime of WSNs. A sensor node can be in the off-duty cycle or can enter power-save mode to conserve battery power. We refer to a sensor node that is in duty to sense its surroundings as an active sensor node and to a sensor that is off duty or enters power-save mode as an inactive sensor node. In a densely deployed WSN, since multiple sensor nodes may cover a subarea or a target, it may not affect the coverage to deactivate and activate sensor nodes alternatively; however, the lifetime of the WSN will be extended.

In recent work concerning network coverage problems where sensor nodes are deployed randomly, researchers assume that the spatial distributions of sensor nodes are known when evaluating their proposed algorithms or protocols. For instances, in [86], the coordinates of sensor nodes are generated using the pseudo-uniform distribution in an area; in [49], sensor nodes are deployed randomly with the Poisson distribution in a barrier.

Previous work using given sensor node distributions provides deep insight into the performance of the WSNs. However, the sensor node distributions may either not hold true or be difficult to obtain beforehand in some applications. For example, for battle field surveillance, sensor nodes can be airdropped either by aircrafts or by rockets. The sensor nodes are distributed along the route of an aircraft when the sensors are dropped by the aircraft, while the sensors are usually within a circle centered under the location where the rocket releases the sensors when

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a rocket is used. In either of these two cases, sensor nodes will not distribute uniformly in the desired sensing field. Instead, more sensors are expected to be found along the route of the aircraft or close to the center of the circle. Moreover, due to wind and other factors, such as environmental, human, and mechanical factors, the distributions of sensor nodes can be difficult to determine beforehand.

There are a few potential disadvantages when sensor node distributions are assumed to be known beforehand. (1) It is very difficult to choose an accurate sensor node location distribution; (2) inaccurate distribution assumption will result in poor analysis of protocols or algorithms; and (3) changes in sensor node distributions may lead to variations in system performance and may sometimes even invalidate the whole analysis.

Motivated by this intuition, we propose a network coverage analysis approach in which no assumption on sensor location distribution is required beforehand. Thus, the approach is in effect a distribution-free approach. The approach is suitable to solve network coverage problems concerning a great number of sensors which are deployed randomly.

The contributions of this work are three-fold. First, we provide an evaluation on the effects of sensor location distribution via both analytical modeling and computer simulations. Our results show that inaccurate sensor location distribution can lead to non-neglectable error of network coverage estimation. Second, we then propose a distribution-free sensor network modeling approach, in which, we take a small sample of the actual deployment, and then apply Kernel-Density Estimator (KDE), a non-parametric statistical analysis, to capture the distribution of the deployment. In practice, this small sample could be a set of enhanced sensor nodes with GPS receivers, and thus their locations can be known after deployment. Based on the estimated sensor node distribution knowledge, the network coverage metrics can be calculated. The last, but not the least, we verify the proposed approach by using our previous work in [106] as an example and the analytical and simulation results show that the distribution-free approach leads to much accurate estimation of network coverage.

The rest of this paper is organized as follows. Section 2 discusses the related work. Section 3 defines the network coverage problem we are dealing with: randomized scheduling algorithm and coverage intensity. In this section, we also formulate the coverage intensity using general probability distribution, in other words, no assumption on sensor location distribution is assumed. We propose the distribution-free approach in Section 4. We use computer simulations to verify the coverage intensity formulization using general probability distribution in Section 5. Section 6 studies the impacts of sensor location distribution on network coverage estimation, and shows that inaccurate sensor location distributions can render network coverage estimation worthless. In Section 7, we present a concrete example to demonstrate the application and effectiveness of the distribution-free approach. We conclude our paper in Section 8 with a summary of findings and a brief discussion of future work.

2. Related work

A sensor network may contain a large number of simple sensor nodes. Sensor nodes are often powered by batteries, and hence have to operate on limited energy budgets. Furthermore, it is difficult to replace batteries in the sensors deployed in inaccessible or inhospitable environments. Thus, many research efforts have studied the energy conservation of sensor nodes to extend sensor network life time [101]. The network lifetime is defined as the time between the initialization of the network and the first case of battery exhaustion among sensor nodes. Extending the network lifetime has been extensively studied [77,16,67]. Many protocols keep a subset of sensor nodes vigilant for sensing and communication tasks while putting the others in power-save mode [1]. On the other hand, energy efficiency should not be achieved at the cost of reduced network coverage and connectivity. Thus, the network coverage and connectivity have also been considered simultaneously in some studies [64,31,102,111].

In [81], the authors studied a network with sensor nodes deployed strictly in grids. A great deal of work focuses on sensor networks, in which sensor locations follow a Poisson point process and sensors are uniformly distributed in sensing fields (e.g., [9,103]). In [76], barrier coverage problems are studied when sensors are distributed along the line with random offsets due to wind and other environmental factors. In [111], the authors investigate energy efficiency in more general sensor networks where the sensor nodes are deployed randomly. In [106], the authors study a randomized scheduling algorithm where sensors are uniformly distributed. Paper [69] proposes a worst and average case algorithm for coverage calculation from the perspective of computational geometry where no sensor location distribution is required. Nevertheless, little work has been done where no prior knowledge of sensor node location distribution is required.

Sensor nodes can be deployed incrementally. The deployment approach proposed in [55] adds sensor nodes one at a time into the network in the most energy-efficient way identified. It is a greedy algorithm that avoids combinatory complexity while providing possible sub-optimal deployment for minimizing power consumption for communications. In [37], an incremental deployment algorithm deploys nodes one at a time such that network coverage is maximized while full line-of-sight connectivity is maintained. The algorithm utilizes information gathered by previously deployed nodes to determine the deployment location of a node. Both current and incremental deployment methods are proposed in [47]. Relying on geometric sampling theory, it provides a lower bound of the number of sensors required for coverage and connectivity. There is also other related work in [109,99,25,42,20,43,93,92,29,65,27,108,19,45,57,28,12,62,10,113,73,75,89,59,90,24,74,88,22,68,23,91,48,116,18,94,7,52,30,71,72,84,100,58,61,97,117,60,6,66,95,63,53,50,80,83,34,112,11,114,96,41,98,21,4,46,107,105,85,87,33,5,56,79,44,3,54,32]

Our approach differs from previous work. This paper studies the impact of sensor location distributions on network coverage and provides a distribution-free approach in which no assumption of sensor location distribution is required and sensor locations can be in any distribution. To the best of our knowledge, no existing literature applies the distribution-free approach to sensor network coverage problems.

3. Coverage intensity

As indicated in [69,15], the concept of WSN coverage (network coverage) has a wide range of interpretations due to a variety of sensors and applications. As a result, many different coverage formulations have been proposed. We provide a network coverage formulation by defining the concept of network coverage intensity and by formulizing the coverage intensity using general probability distribution. In other words, we formulize the coverage intensity without using actual sensor location distribution as a priori. To show the impacts of sensor location distributions, we then study and compare the network coverage intensity of a few sensor location distributions in Section 6. To verify the effectiveness of our distribution-free approach, we need to compare the coverage intensity estimation obtained by using the distribution-free approach with the estimation obtained when actual distributions are known in Section 7. Therefore, we apply the formula of coverage intensity derived using general probability distribution to three specific probability distributions to obtain the corresponding results used in Sections 6 and 7.

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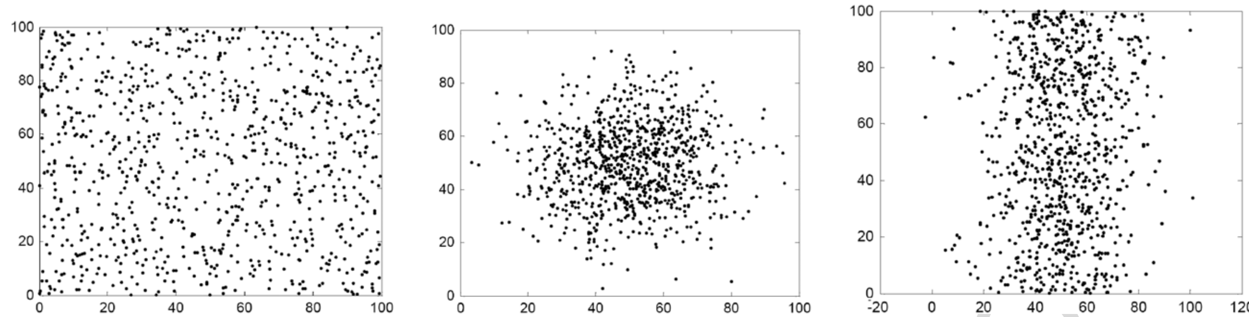

(a) Uniform distribution. (b) Gaussian distribution. (c) GU distribution.

Fig. 1. Sensor node location distributions.

3.1. Coverage intensity

Assume that n sensors are randomly deployed to form a wireless sensor network to cover a field, which we refer to as the sensing field. The sensor network runs a randomized scheduling algorithm. The randomized scheduling algorithm is given as follows. Let S denote the set of all the n sensor nodes. Let S be divided into k disjoint subsets S_j ($j = 1, 2, \dots, k$) with each sensor node being randomly assigned to one of these subsets. At any time, only one subset of sensor nodes is active and the rest are inactive. The objective is to extend the network lifetime and maintain satisfactory coverage. We measure the coverage using coverage intensity.

Network coverage intensity is the ratio of the time when a point in the field of the sensor network is covered by at least one active sensor node to the total time. We model the sensor node deployment field as a two-dimensional Cartesian coordination system. The field ranges from 0 to X and from 0 to Y on the X- and Y-axes, respectively. Assume that the sensing area of a sensor is the area of a circle and the sensing range of sensors is R, the radius of the circle. Let $f(x, y)$ denote the probability density function of sensor node locations. Actual deployment of sensor nodes may be unknown, and $f(x, y)$ can be any distribution. Let $P(g, h)$ denote the probability that a given point, (g, h), is covered by at least one sensor node. We have

$$P(g, h) = \iint_{(x-g)^2+(y-h)^2 \le R^2} f(x, y)\mathrm{d}x\mathrm{d}y. \tag{1}$$

Since n sensors are divided into k disjoint subsets, which take turns waking up and performing sensing tasks while the rest of the subsets are in power-save mode. Then the probability that point (g, h) is covered by an active sensor can be written as

$$C(g, h) = 1 - [1 - P(g, h)/k]^n. \tag{2}$$

Coverage intensity is the detection metric for the whole network. Note that point (g, h) is randomly chosen from the sensing field. Thus, the network coverage intensity for the network is

$$C_n = E(C(g, h)). \tag{3}$$

It is worth noting that, in the above discussion, no assumption of sensor location distribution is given, and that the sensor location distribution can be any distribution, even one which has no explicit form.

The above derivation does not consider the edge effect. Since the whole sensing field must have boundaries, the coverage area of a sensor node may not be completely inside the sensing field, which we refer to as the edge effect. The computer simulations in Section 5 show that the error rate between the simulation and analytical results is very small and can be neglected when the number of sensors is large.

3.2. Uniform distribution

Assume that sensors are uniformly deployed in the sensing field. Fig. 1(a) shows an example deployment. This case is studied in detail in [106]. For comparison purposes, we reformulate the coverage intensity using the result obtained in the previous subsection. Sensor location (g, h) follows a two-dimensional uniform distribution, namely $f(x, y) = 1/(XY)$. By plugging this into Eqs. (1)–(3), we can obtain the network coverage intensity of the two-dimensional uniform distribution.

$$P^U(g, h) = \iint_{(x-g)^2+(y-h)^2 \le R^2} \frac{1}{XY}\mathrm{d}x\mathrm{d}y = \frac{\pi R^2}{XY} \tag{4}$$

$$C^U(g, h) = 1 - \left[1 - \frac{\pi R^2}{kXY}\right]^n \tag{5}$$

$$\begin{aligned} C_n^U &= E(C(g, h)) \\ &= \int_0^Y \int_0^X \frac{1}{XY} \left\{1 - \left[1 - \frac{\pi R^2}{kXY}\right]^n\right\} \mathrm{d}x\mathrm{d}y \\ &= 1 - \left[1 - \frac{\pi R^2}{kXY}\right]^n \end{aligned} \tag{6}$$

where we use superscript U to indicate that sensor locations follow a two-dimensional uniform distribution.

3.3. Two-dimensional Gaussian distribution

Assume that sensor nodes deployed in the sensing field follow a two-dimensional Gaussian distribution. Fig. 1(b) shows an example deployment. The probability density function of the two-dimensional Gaussian distribution is given as

$$f(x, y) = \frac{1}{2\pi\sigma^2} \mathrm{e}^{-[(x-X/2)^2+(y-Y/2)^2]/2\sigma^2}.$$

Plugging this into (1), we have

$$P^G(g, h) = \iint_{(x-g)^2+(y-h)^2 \le R^2} \frac{1}{2\pi\sigma^2} \mathrm{e}^{-[(x-X/2)^2+(y-Y/2)^2]/2\sigma^2}\mathrm{d}x\mathrm{d}y$$

where subscript G indicates that sensor locations follow a two-dimensional Gaussian distribution.

Let $x' = x - g$ and $y' = y - h$,

$$P^G(g, h) = \iint_{x'^2+y'^2 \le R^2} \frac{1}{2\pi\sigma^2} \mathrm{e}^{-[(x'+g-X/2)^2+(y'+h-Y/2)^2]/2\sigma^2}\mathrm{d}x'\mathrm{d}y'.$$

Let $x' = l\sin\theta, y' = l\cos\theta$, and $|J| = |\frac{\partial(x', y')}{\partial(l, \theta)}| = l$,

$$\begin{aligned} &P^G(g, h) \\ &= \int_0^R \int_0^{2\pi} \frac{1}{2\pi\sigma^2} \mathrm{e}^{-[(l\sin\theta+g-X/2)^2+(l\cos\theta+h-Y/2)^2]/2\sigma^2} |J|\mathrm{d}l\mathrm{d}\theta \\ &= \int_0^R \int_0^{2\pi} \frac{1}{2\pi\sigma^2} \mathrm{e}^{-[(l\sin\theta+g-X/2)^2+(l\cos\theta+h-Y/2)^2]/2\sigma^2} l\mathrm{d}l\mathrm{d}\theta. \end{aligned} \tag{7}$$

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Plug (8) into (2) and (3), and we have

$$C^G(g,h) = 1 - [1 - P^G(g,h)/k]^n \tag{8}$$

$$C_n^G = E(C^G(g,h)). \tag{9}$$

3.4. GU distribution

In this subsection, we assume that the known sensor location distribution is the one along the x-axis, where sensor locations follow a Gaussian distribution with a mean of $X/2$, and along the y-axis, where sensor locations follow a uniform distribution with a mean of $Y/2$. Fig. 1(c) shows an example deployment. For simplicity, we name this two-dimensional distribution as a GU distribution. As in the above, we need to calculate the probability $P(g,h)$ to obtain coverage intensity under a GU distribution. Thus, we have

$$P^{GU}(g,h) = \iint_{(x-g)^2+(y-h)^2 \le R^2} f(x)f(y)\mathrm{d}x\mathrm{d}y$$

where $f(x) = \frac{1}{\sqrt{2\pi}\sigma_x} \mathrm{e}^{-\frac{(x-X/2)^2}{2\sigma_x{}^2}}$ and $f(y) = \frac{1}{Y}$. Note that superscript GU indicates that sensor locations follow a GU distribution.

Following steps similar to those in the previous subsection, we have

$$P^{GU}(g,h) = \int_0^R \int_0^{2\pi} \frac{1}{\sqrt{2\pi}\sigma_x} \mathrm{e}^{-\frac{(l\sin\theta+g-X/2)^2}{2\sigma_x{}^2}} \frac{1}{Y} l\mathrm{d}l\mathrm{d}\theta \tag{10}$$

$$C^{GU}(g,h) = 1 - [1 - P^{GU}(g,h)/k]^n \tag{11}$$

$$C_n^{GU} = E(C^{GU}(g,h)). \tag{12}$$

4. Distribution-free approach

In this section, we introduce the distribution-free approach for estimating coverage intensity. The approach uses a non-parametric statistical method [35,13]. It does not require the sensor location distribution to be known. Instead, it requires the locations of a few sensors among the deployed sensors.

There are many studies regarding sensor node localization. Common localization approaches [8,14,36,51,70,82] rely on a few sensor anchor or beacon nodes whose locations are known in advance, e.g., via GPS signals. Thus, we can have a few sensors whose locations can be accurately determined. Due to random factors in the real world, such as wind, it is impossible for sensor location distributions to be exactly the same as assumed distributions. Since inaccurate knowledge of sensor location distributions can yield misleading or invalid network coverage estimations, we propose a distribution-free approach to estimate the network coverage intensity. The approach is not based on an assumed distribution. Instead, it is based on the locations of a sample of sensor nodes whose locations are known.

In the rest of this section, we first present how we infer sensor location distribution from the locations of a sample of sensor nodes using a non-parametric statistical method, called kernel-density estimation [35,13]. KDE is one of the mostly used non-parametric techniques. It provides an estimation of arbitrary distribution from empirical data without much prior knowledge. KDE-based methods have been shown to be robust and effective methods in distributed systems and computer networks [39,115, 40]. Although other non-parametric statistical methods exist and are worth investigating, as a step forward, we focus our effort on evaluating the effectiveness of KDE-based method for scheduling and coverage problem in large sensor networks.

4.1. Infer sensor location distribution from locations of sample sensor nodes

Denote the locations of randomly selected sample nodes as $(X_i, Y_i), i = 1, 2, \ldots, N$, where N is the sample size. From [35], the probability density at any point (x,y) can be estimated using the locations of the sample of sensor nodes, i.e.,

$$\hat{f}_h(x,y) = \frac{1}{Nh_xh_y} \sum_{i=1}^{N} K\left(\frac{x-X_i}{h_x}, \frac{y-Y_i}{h_y}\right) \tag{13}$$

where $K(\bullet)$ is some kernel and h_x and h_y are smoothing factors or window-width. $K(\bullet)$ is often taken to be a standard Gaussian function with mean 0 and variance 1, i.e.,

$$K(u,v) = \frac{1}{2\pi}\mathrm{e}^{-\frac{1}{2}(u^2+v^2)}. \tag{14}$$

Plugging (14) into (13), we obtain

$$\begin{aligned}\hat{f}_h(x,y) &= \frac{1}{Nh_xh_y} \sum_{i=1}^{N} K\left(\frac{x-X_i}{h_x}, \frac{y-Y_i}{h_y}\right) \\ &= \frac{1}{Nh_xh_y} \sum_{i=1}^{N} \frac{1}{2\pi} \mathrm{e}^{-\frac{1}{2}\left(\frac{(x-X_i)^2}{h_x^2} + \frac{(y-Y_i)^2}{h_y^2}\right)}.\end{aligned} \tag{15}$$

Note that (1) window-width h_x and h_y indirectly control the variance of the Gaussian function and that (2) probability density functions to be estimated can be multi-modal [13] and by no means have to be Gaussian, even though the kernel is a Gaussian function.

Choices of N, h, and $K(\bullet)$ are the factors determining the efficiency and effectiveness of the estimation of the probability density.

4.2. Distribution-free coverage intensity estimation

The approach has four steps: (1) obtaining the locations of the sample sensor nodes; (2) analyzing the locations and obtaining the window-width (h_x and h_y); (3) approximating sensor location distribution using kernel-density estimation; (4) calculating the coverage intensity based on the Kernel-density estimation.

Though N and $K(\bullet)$ are also factors related to the efficiency and effectiveness of the approach, they are determined empirically before sensor deployment in this paper. The above four steps are carried out after sensor deployment without using any assumed sensor location distribution.

The coverage intensity is calculated as follows. Replacing $f(x,y)$ in (1) by (13), we obtain

$$\begin{aligned}P^{DF}(g,h) &= \iint_{(x-g)^2+(y-h)^2 \le R^2} \hat{f}_h(x,y)\mathrm{d}x\mathrm{d}y \\ &= \iint_{(x-g)^2+(y-h)^2 \le R^2} \frac{1}{Nh_xh_y} \\ &\quad \times \sum_{i=1}^{N} K\left(\frac{x-X_i}{h_x}, \frac{y-Y_i}{h_y}\right) \mathrm{d}x\mathrm{d}y\end{aligned} \tag{16}$$

where superscript DF indicates that we are using the distribution-free approach. Plugging (16) into (2) and (3), we have

$$C^{DF}(g,h) = 1 - [1 - P^{DF}(g,h)/k]^n \tag{17}$$

$$C_n^{DF} = E(C^{DF}(g,h)). \tag{18}$$

5. Simulation verification

In this section, we perform computer simulations to verify the analytical model presented in Section 3. We developed our own

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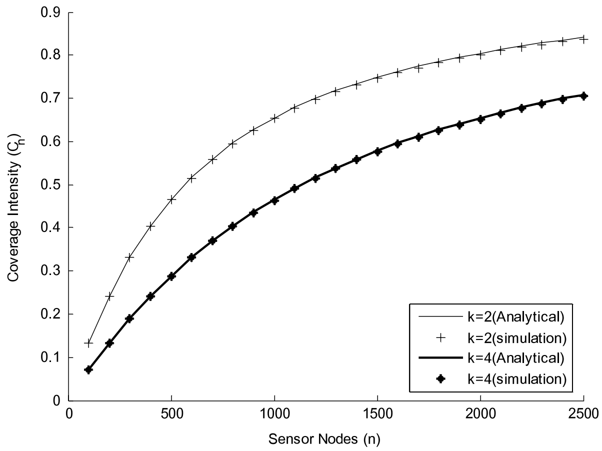

Fig. 2. Coverage intensity *vs.* number of sensor nodes.

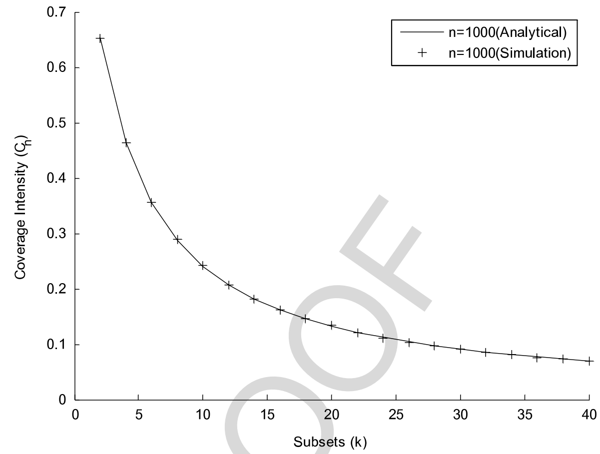

Fig. 3. Coverage intensity *vs.* number of subsets.

simulation program in C++. The program is an implementation of discrete event simulation. The locations of sensors and intrusions are either derived from a given distribution or loaded from a given sensor node configuration. There are three types of events, intrusion events, detection events, and intrusion departure events. An intrusion event is generated randomly. A detection event occurs when the associated intrusion event is detected by at least one sensor node. The departure event is generated whenever the lifetime of the intrusion event expires. In our simulations below, sensor nodes are deployed randomly in the sensing field. The purposes of this section are to demonstrate that (1) the analytical model in Section 3 is accurate, and that (2) the edge effect is neglectable. To cope with limited space, we show only the results for GU distributions for the first purpose. For the second purpose, we show only the results for the two-dimensional uniform distributions.

In this section, the standard deviation (σ_x) of Gaussian distribution along the x-axis is 20, the number of deployed sensor nodes (n) is 1000, the size of the whole sensing field is 10 000, the sensing area of each sensor is 30, and the number of subsets is 4, unless otherwise stated.

Fig. 2 shows the network coverage intensity *vs.* the number of sensor nodes with both analytical and simulation results. The figure shows that the analytical results match the simulation results exactly. In addition, the network coverage intensity increases as the number of sensor nodes increases, and the network coverage intensity becomes smaller as the number of disjointed subsets (k) increases.

Fig. 3 shows the coverage intensity *vs.* the number of disjoint subsets (k) with both analysis and simulation. The figure shows that the analytical and simulation results match exactly. Additionally, the network coverage intensity decreases as the number of subsets increases, and the network coverage intensity goes to 0 as the number of disjointed subsets goes to infinity.

Fig. 4 shows the coverage intensity *vs.* the standard deviation of Gaussian distribution along the x-axis with both analytical results and simulation results for different numbers of subsets. This figure shows that the analytical results match the simulation results exactly. Furthermore, the network coverage intensity first increases and then decreases as the value of standard deviation increases. A larger k value makes the network coverage intensity smaller. When the value of standard deviation goes to infinity, the network coverage intensity goes to 0. The reason for this trend is that, the larger the standard deviation becomes, the lower the probability that the sensor can be deployed in the designated sensing field becomes.

Fig. 5 shows that the error rate between the simulation results and the analytical results is less than 5% when $n = 50$, and much

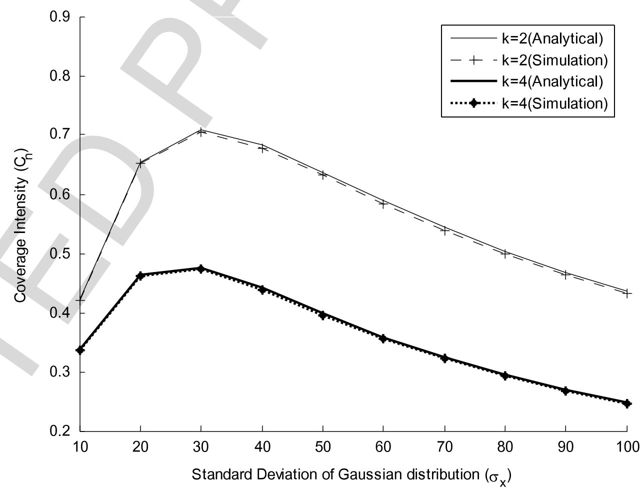

Fig. 4. Coverage intensity *vs.* standard deviation.

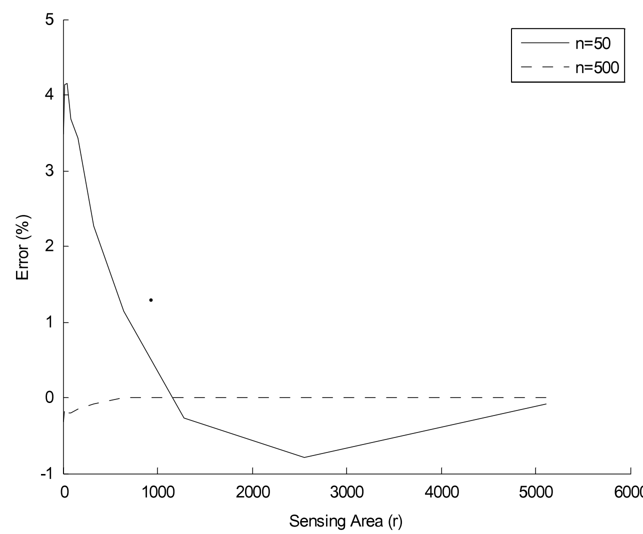

Fig. 5. Error of coverage intensity between analytical and simulation results.

less than 1% when $n = 500$. Error rate is defined as $\left(C_n^a - C_n^s\right)/C_n^s$, where C_n^a and C_n^s denote the coverage intensity obtained from (6) and from computer simulations, respectively. It is clear that when the number of sensors is large enough, the error caused by the edge effect can be neglected.

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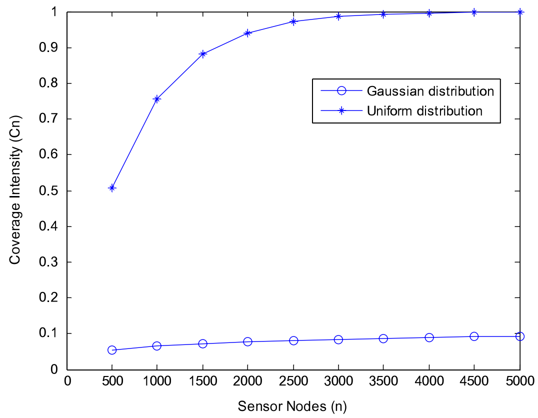

Fig. 6. Coverage intensity *vs.* number of sensor nodes ($k = 2$, $\sigma = 5$).

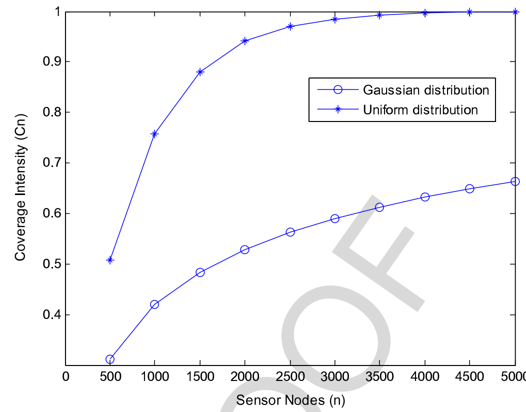

Fig. 7. Coverage intensity *vs.* number of sensor nodes ($k = 2$, $\sigma = 15$).

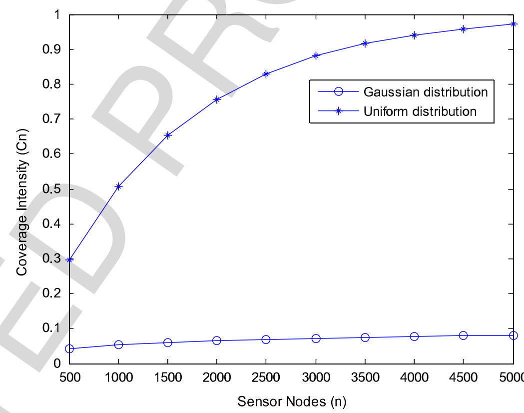

Fig. 8. Coverage intensity *vs.* number of sensor nodes ($k = 4$, $\sigma = 5$).

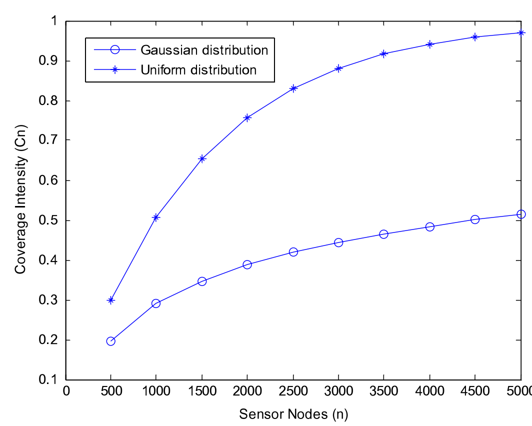

Fig. 9. Coverage intensity *vs.* number of sensor nodes ($k = 4$, $\sigma = 15$).

6. Impacts of sensor node location distribution on network coverage estimation

In this section, we show the impacts of inaccurate sensor location distribution on network coverage estimation. Intuitively, the discrepancy between actual and estimated network coverage would occur when the knowledge of the sensor location distribution is inaccurate. We intend to demonstrate that the discrepancy is so great that the inaccurate sensor location distributions may in effect render the network coverage estimation worthless and misleading. This section is organized as follows. (1) We compare the calculated coverage intensity when sensor location distributions are uniform and two-dimensional Gaussian respectively. This case can be interpreted to mean that the actual sensor location distribution is a two-dimensional Gaussian distribution; however, we assume that the distribution is uniform, or vice versa. (2) Similarly, we next compare the calculated coverage intensity of uniform and GU distributions.

The coverage intensity for uniform distributions is calculated using Eq. (6), that for two-dimensional Gaussian distributions using Eq. (9), and that for GU distributions using Eq. (12). We choose $X = 100$, $Y = 100$, and $R = 3$ unless otherwise stated.

6.1. Two-dimensional Gaussian and Uniform distributions

Figs. 6–9 show the coverage intensity *vs.* the number of sensor nodes for both Gaussian and Uniform distributions, when the number of disjoint subsets k and the standard deviation of Gaussian distributions σ vary. The discrepancy of coverage intensity between Gaussian and Uniform distributions when $\sigma = 5$ is greater than that when $\sigma = 15$. Regardless of whether $\sigma = 5$ or 15, the discrepancy of coverage intensity between the two distributions is apparent. Note that when the number of sensors goes to infinity, the coverage intensity of Uniform distribution goes to 1, but the coverage intensity of Gaussian distribution increases much more slowly.

Figs. 10 and 11 show the coverage intensity *vs.* standard deviation of Gaussian distributions. A large discrepancy between uniform and Gaussian distributions can be found when σ is either very small or very large. The reason is that sensors are concentrated at the center of the sensing field when σ is very small and many areas of the field are not covered, and many sensors will be deployed outside of the sensing field when σ is very large.

6.2. Gu and Uniform distributions

Figs. 12–15 show the coverage intensity *vs.* the number of sensor nodes for both GU and Uniform distributions, when the number of disjoint subsets k and the standard deviation of Gaussian distributions for x-axis σ_x vary. The discrepancy of coverage intensity between GU and Uniform distributions when $\sigma_x = 5$ is greater than that when $\sigma_x = 15$. Regardless of whether in either case, the discrepancy of coverage intensity between two distributions is apparent. Note that, when the number of sensors goes to infinity, the coverage intensity of Uniform distribution goes to 1 but the coverage intensity of GU distribution increases more slowly.

Figs. 16 and 17 show the coverage intensity *vs.* standard deviation of Gaussian distribution. A large discrepancy between uniform and Gaussian distributions can be found when σ_x is either very small or very large. The reason is that sensors are concentrated at the center of the sensing field when σ_x is very small, and many

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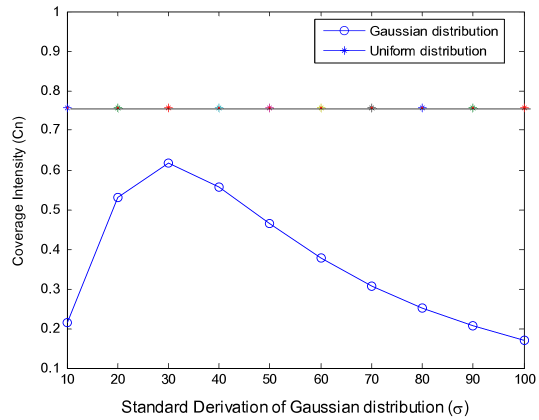

Fig. 10. Coverage intensity *vs.* standard deviation ($n = 1000$).

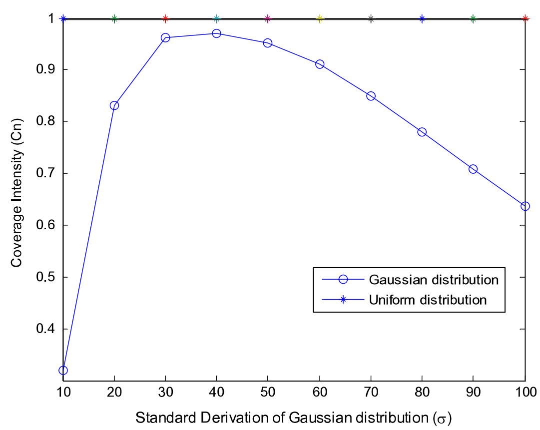

Fig. 11. Coverage intensity *vs.* standard deviation ($n = 5000$).

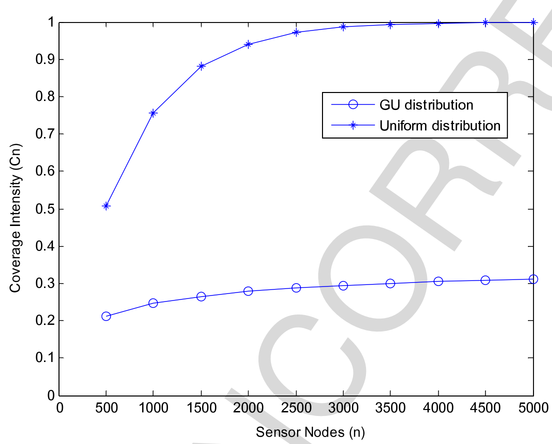

Fig. 12. Coverage intensity *vs.* number of sensor nodes ($k = 2, \sigma = 5$).

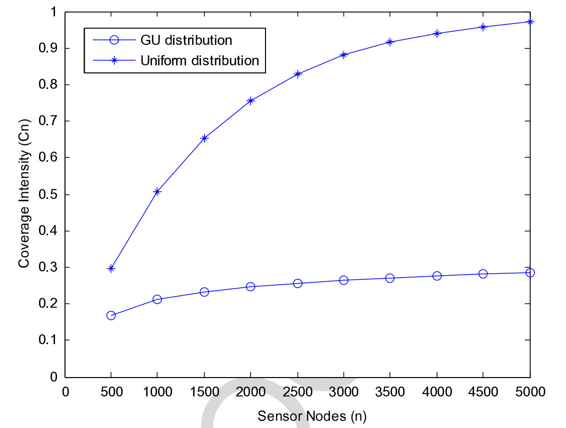

Fig. 13. Coverage intensity *vs.* number of sensor nodes ($k = 4, \sigma = 5$).

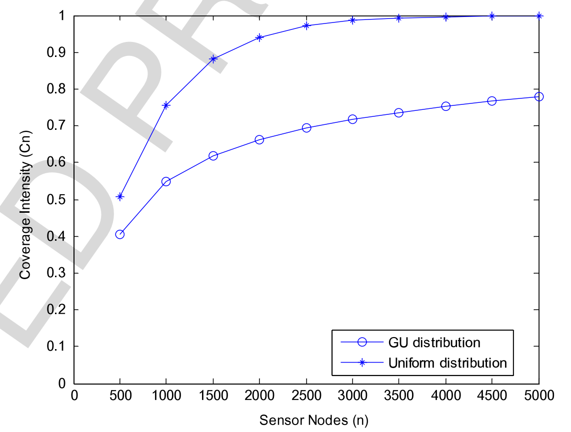

Fig. 14. Coverage intensity *vs.* number of sensor nodes ($k = 2, \sigma = 15$).

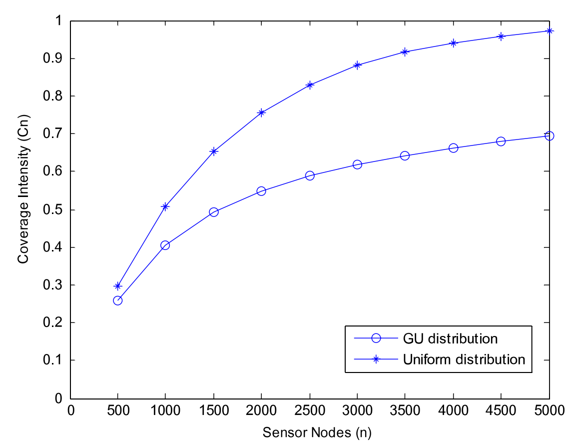

Fig. 15. Coverage intensity *vs.* number of sensor nodes ($k = 4, \sigma = 15$).

areas of the field are not covered, and many sensors will be deployed outside of the sensing field when σ is very large.

6.3. Deploy-once and re-deploy

Fig. 18 shows the simulation results of the coverage intensity *vs.* the standard deviation of Gaussian distribution along the *x*-axis under two different deployment assumptions. The first assumes that the sensor deployment follows a GU distribution. Under this assumption, the sensor nodes can be deployed either within the intended sensing field or outside of the field. In the second assumption, after deploying a set of sensor nodes, we collect those sensor nodes which are outside the intended sensing field and re-deploy them. We repeat this procedure until all sensor nodes are deployed in the designated sensing field. As illustrated in the figure, the network intensity is larger under the second assumption. This figure also shows that the discrepancy of coverage intensity caused by different assumptions can be large.

From the above three cases, we can conclude that the discrepancy of network coverage generated by inaccurate probability distributions is very large and cannot be neglected.

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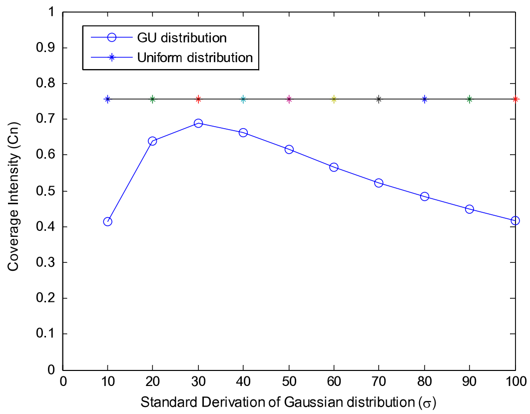

Fig. 16. Coverage intensity *vs.* standard deviation ($n = 1000$).

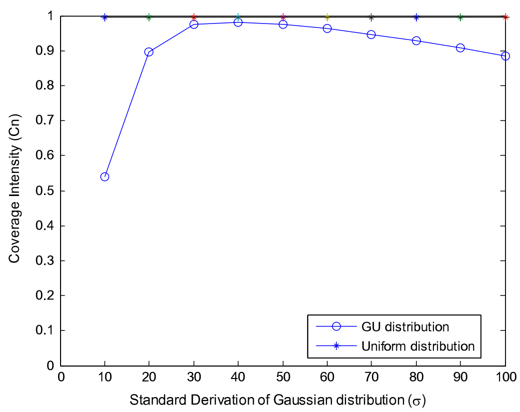

Fig. 17. Coverage intensity *vs.* standard deviation ($n = 4000$).

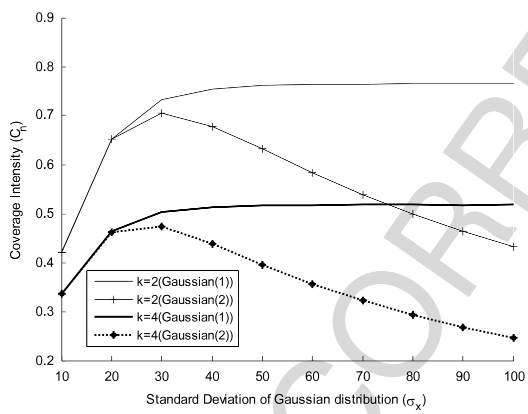

Fig. 18. Comparison of two deployment strategies: deploy-once and re-deploy.

7. Example and evaluation of distribution-free approach

In this section, we demonstrate how to apply the distribution-free approach to estimate network coverage intensity. As discussed in Section 4, three factors affect the effectiveness and efficiency of the approach. The three factors are kernel $K(\bullet)$, sample size N, and windows-widths h_x and h_y. Literature has shown that Gaussian function is a good choice for estimating the probability density of continuous random variables using the kernel-density estimation method [13]. Note that probability density functions to be estimated can be multi-modal and by no means have to be Gaussian, though the kernel is a Gaussian function. Nevertheless, we have to determine sample size and windows-widths beforehand. In Section 7.1, we present some discussion on the sample size and the window-width. In Section 7.2, we present a complete example of the distribution-free approach and compare the result obtained from the distribution-free approach with that obtained from actual distribution.

7.1. Sample size and window-width

7.1.1. Sample size

A larger number of sample sensor nodes leads to better estimation of network coverage. A large sample can be obtained by deploying large numbers of anchor or beacon sensor nodes, or by determining accurate locations of a large number of sensor nodes, which is difficult to do. However, when too few sample sensor nodes are chosen, the network coverage estimation can be inaccurate. In this paper, we use a simple method to determine the sample size. The main idea is to choose a sample size so that the difference of the sample mean and the population mean is within a threshold with a large probability or confidence. The method requires many field experiments and proceeds as follows,

1. Deploy N sensors in a sensing field via a desirable vehicle, e.g., an aircraft or a rocket. Obtain the locations of all the sensors. The sensors are treated as a population, and we calculate the mean and the variance of the locations of the sensors. Denote the population mean and the population variance as $\bar{Y}$ and S^2 respectively.
2. Randomly select a small number of sensors. The sensors constitute a sample. Obtain their locations. Calculate the mean and the variance of the locations. Denote the sample mean and the sample variance as $\bar{y}$ and s^2, respectively.
3. Calculate the error between the sample mean and the population mean, and denote it as $r = (\bar{y} - \bar{Y})/\bar{Y}$.
4. As suggested in [17], the proper sample size is estimated as $n = \left(\frac{u_{\alpha/2}S}{r\bar{Y}}\right)^2 \Big/ \left[1 + \frac{1}{N}\left(\frac{u_{\alpha/2}S}{r\bar{Y}}\right)^2\right]$, where $u_{\alpha/2}$ is the value of the vertical boundary for the area of $\alpha/2$ in the right tail of the standard normal distribution.

Repeat the above steps a few times to reach a consensus.

The work of deciding sample size is implemented in a test field where we can easily collect the data of sensor locations. In reality, the sensor network is usually deployed in a hostile field or a rough area where it is hard to collect the locations of many sensors. However, based on the result of sample size obtained from our experiment in the test field, we can choose a small group of sensors as samples before the real deployment and equip these sample sensors as beacons which have the functions to know their coordinates after deployment from satellite information [78]. After deployment in reality, we can estimate the distribution of sensor deployment based on sample sensor locations which will introduce in the following section.

7.2. Window-width

For simplicity, let $h_x = h_y = h$ in this subsection. In the following, we will show the impact of window-width (h) for the coverage intensity estimation in three different cases, (1) two-dimensional Gaussian distribution, (2) two-dimensional Uniform distribution, and (3) GU (X-Gaussian Y-Uniform) distribution.

Fig. 19 shows the probability density function of two-dimensional Gaussian distribution on the whole sensing field. Fig. 20 shows the estimated distribution when window-width (h) is chosen as 1. From the figure, we can see many interferences. From Fig. 22, where the window-width (h) is chosen as 25, we can see that the estimation is too flat because we ignore too much random interference in locality. Finally, from Fig. 21, where the window-width (h) is chosen as 10, we see that the approximated estimation is the best.

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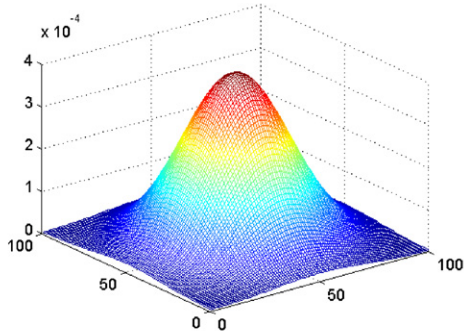


Fig. 19. Two-dimensional Gaussian distribution.

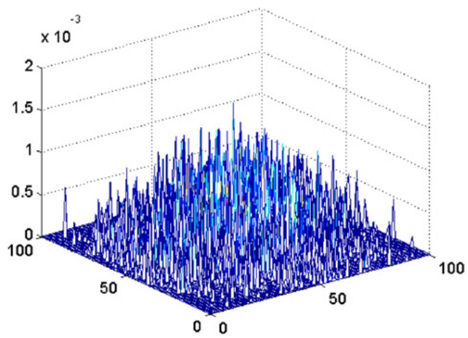


Fig. 20. Estimation (window-width $(h) = 1$).

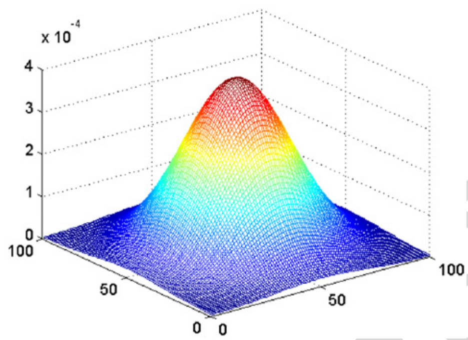


Fig. 21. Estimation (window-width $(h) = 10$).

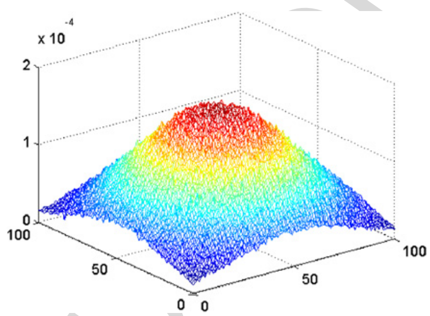


Fig. 22. Estimation (window-width $(h) = 25$).

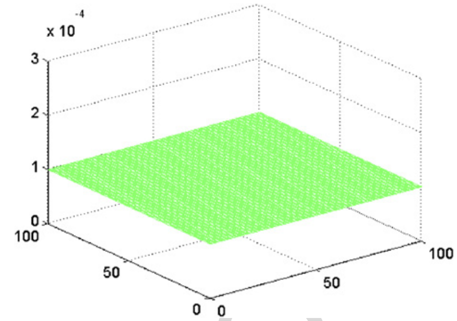


Fig. 23. Two-dimensional uniform distribution.

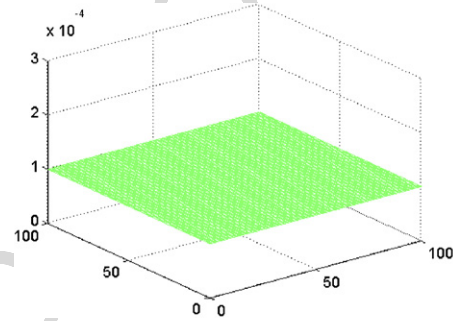


Fig. 24. Estimation (window-width $(h) = 1$).

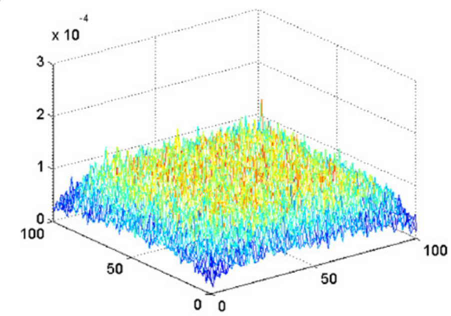


Fig. 25. Estimation (window-width $(h) = 10$).

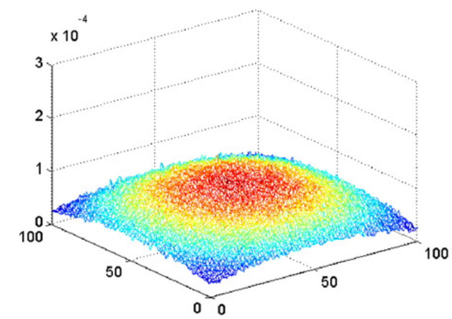


Fig. 26. Estimation (window-width $(h) = 25$).

Fig. 23 shows two-dimensional uniform distribution on the whole sensing field. Fig. 24 shows the estimated density function when window-width (h) is chosen as 1. From the figure, we can see many interferences. From Fig. 26, where the window-width (h) is chosen as 25, we can see that the estimation is too curved because we ignore too much random interference in locality. Finally, from Fig. 25, where the window-width (h) is chosen as 10, we see that the approximated estimation is the best.

Fig. 27 shows GU distribution on the whole sensing field. Fig. 28 shows the estimated distribution when window-width (h) is chosen as 1. From the figure, we can see many interferences. From Fig. 30, where the window-width (h) is chosen as 25, we can see that the curve face is too flat because we ignore too much random interference in locality. Finally, from Fig. 29, where the window-width (h) is chosen as 10, we see that the approximated estimation is the best.

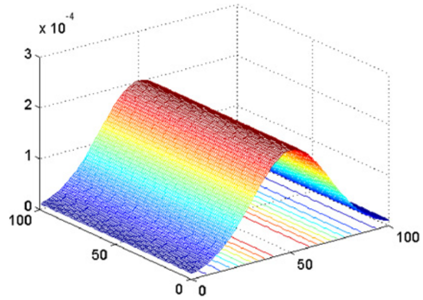


Fig. 27. *x*-Gaussian, *y*-uniform distribution.

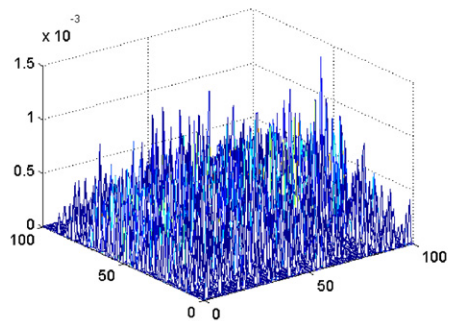


Fig. 28. Estimation (window-width $(h) = 1$).

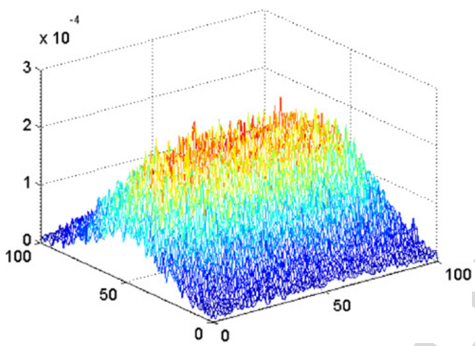


Fig. 29. Estimation (window-width $(h) = 10$).

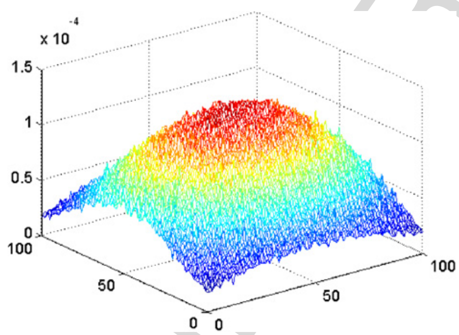


Fig. 30. Estimation (window-width $(h) = 25$).

7.3. Example and evaluation of distribution-free approach

7.3.1. Step 1: obtain locations of sample sensors

First, before deployment, according to the number of sensor nodes deployed in the sensor network, we decide how many samples we need to provide based on the results obtained from the sample size section. Then we randomly choose the number of sample nodes and set them as anchor nodes. Second, after random deployment, the sample sensors' location coordinates can be obtained via a sensor localization protocol. Here, the locations of the sample sensors are $(X_i, Y_i), i = 1, 2, \ldots, N$, where N is the sample size. Table 1 shows an example of the locations of the sample sensors. In the example, the whole deployment area is $X \times Y = 100\text{ m} \times 100\text{ m}$, the sensing area of each sensor is 30 m^2, the number of sample sensor nodes is $N = 50$, and the standard deviation of GU distribution along the *x*-axis is 5.

Table 1
Locations of sample sensors.

Sample		Sample	
(X_1, Y_1)	44.95, 19.34	(X_{26}, Y_{26})	48.83, 70.27
(X_2, Y_2)	53.07, 68.22	(X_{27}, Y_{27})	50.59, 54.66
(X_3, Y_3)	52.54, 30.28	(X_{28}, Y_{28})	51.57, 44.49
(X_4, Y_4)	58.46, 54.17	(X_{29}, Y_{29})	57.22, 69.45
(X_5, Y_5)	52.96, 15.09	(X_{30}, Y_{30})	48.25, 62.13
(X_6, Y_6)	46.78, 69.79	(X_{31}, Y_{31})	53.17, 79.48
(X_7, Y_7)	51.90, 37.84	(X_{32}, Y_{32})	53.99, 95.68
(X_8, Y_8)	44.95, 86.00	(X_{33}, Y_{33})	54.70, 52.26
(X_9, Y_9)	49.90, 85.37	(X_{34}, Y_{34})	45.04, 88.01
(X_{10}, Y_{10})	49.76, 59.36	(X_{35}, Y_{35})	51.06, 17.29
(X_{11}, Y_{11})	50.00, 49.66	(X_{36}, Y_{36})	51.19, 97.97
(X_{12}, Y_{12})	48.41, 89.98	(X_{37}, Y_{37})	44.96, 27.14
(X_{13}, Y_{13})	55.48, 82.16	(X_{38}, Y_{38})	46.29, 25.23
(X_{14}, Y_{14})	40.63, 64.49	(X_{39}, Y_{39})	55.41, 87.57
(X_{15}, Y_{15})	52.14, 81.80	(X_{40}, Y_{40})	49.34, 73.73
(X_{16}, Y_{16})	54.48, 66.02	(X_{41}, Y_{41})	51.95, 13.65
(X_{17}, Y_{17})	53.65, 34.20	(X_{42}, Y_{42})	50.44, 1.17
(X_{18}, Y_{18})	52.89, 28.97	(X_{43}, Y_{43})	46.82, 89.39
(X_{19}, Y_{19})	50.20, 34.12	(X_{44}, Y_{44})	47.20, 19.91
(X_{20}, Y_{20})	53.38, 53.40	(X_{45}, Y_{45})	52.22, 29.87
(X_{21}, Y_{21})	52.84, 72.71	(X_{46}, Y_{46})	45.25, 66.14
(X_{22}, Y_{22})	48.72, 30.93	(X_{47}, Y_{47})	53.91, 28.44
(X_{23}, Y_{23})	48.11, 83.85	(X_{48}, Y_{48})	52.84, 46.92
(X_{24}, Y_{24})	48.52, 56.81	(X_{49}, Y_{49})	45.89, 6.48
(X_{25}, Y_{25})	42.62, 37.04	(X_{50}, Y_{50})	48.67, 98.83

7.4. Step 2: window-width (h)

In kernel-density estimation, the window-width plays an important role. Many numerical methods have been developed to find h, and they mostly minimize the so-called Mean Integrated Squared Error [13]. In our experiment, we use a fast and accurate bivariate kernel-density estimator as in [13] to obtain the window-width values (h_x and h_y). For example, based on the sample sensor location data in Fig. 19, the bivariate window-width we obtained is $(h_x, h_y) = (3.88, 16.71)$.

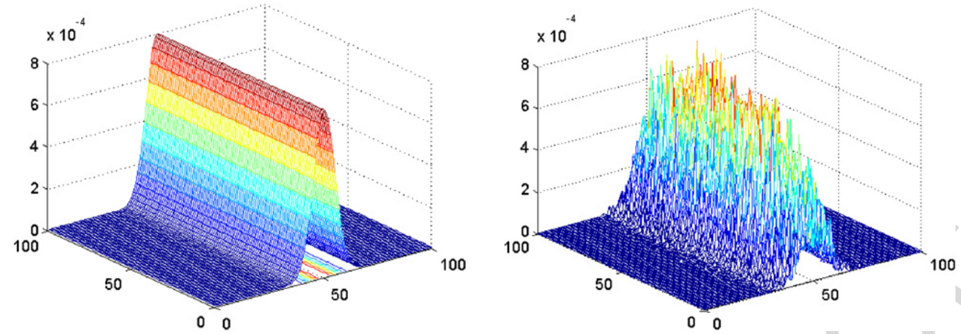
7.5. Step 3: distribution estimation

Based on the sample location coordinates from Step 1 and the bivariate window-width from Step 2, the density function can be calculated using Eq. (15) since we use Gaussian function as the kernel.

The sensor location distribution in the real world (GU distribution) is given in Fig. 31(a), and the estimation based on the locations of sample sensors as shown in Table 1 is given in Fig. 31(b). Through comparing these two distribution figures, we can see that the estimated distribution is quite close to the actual distribution. Note that a better estimation can be achieved by increasing the size of the sample of sensor nodes.

7.6. Step 4: system performance evaluation

In this step, we can use the distribution estimation result to study the network performance metrics of interest. In our experiment, the coverage intensity is the studied network metric. Based on (16)–(18), the estimated coverage intensity can be obtained. Fig. 32 shows the estimation results.



(a) GU distribution (standard deviation = 5).

(b) Distribution estimation.

Fig. 31. Estimation evaluation.

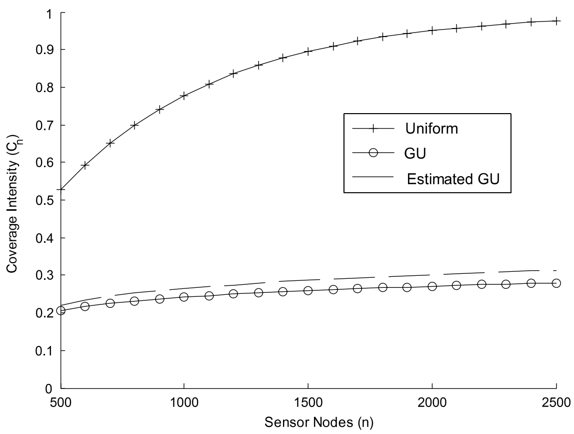


Fig. 32. Estimation performance (size of sample = 50).

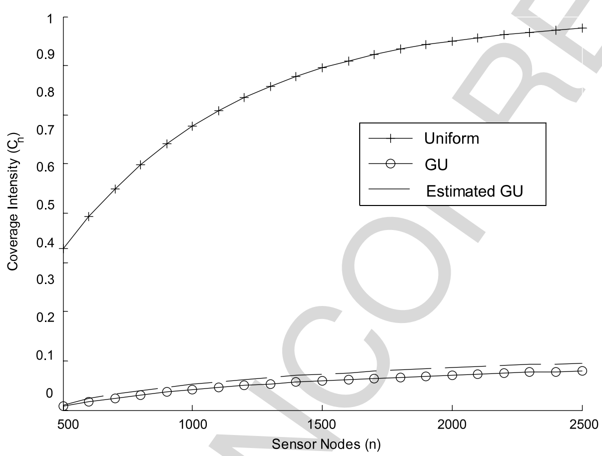


Fig. 33. Estimation performance (size of sample = 100).

Fig. 32 shows the network coverage intensity *vs.* the number of sensor nodes for Uniform distribution, GU distribution, and the Estimated GU distribution, where the standard deviation of Gaussian distribution along the *x*-axis is 5 and the number of disjointed subsets is 2. In the experiment, the size of the whole sensing field is 10 000 and the sensing area of each sensor is 30. In Fig. 32, in the sensor network, the number of whole deployed sensors varies from 500 to 2500; but we only use 50 sample sensors to estimate the distribution through the kernel-density estimation method.

By increasing the size of the sample, we can improve our estimation accuracy, as illustrated in Fig. 33; the estimation of coverage intensity using 100 sensor nodes is better than the performance estimation shown in Fig. 32, where 50 sensor nodes are used.

8. Conclusion and future work

Network coverage is an important problem of WSNs. Previous works are largely based on assumed probability density functions that govern the distribution of sensor nodes in the sensing field. However, the actual distribution of sensor nodes may be very different from the assumed one. Our analytical and simulation study shows that, when a different assumption is used, the introduced error in the network coverage metrics is very large and cannot be neglected.

In this paper, we first reformulated the network coverage intensity using general probability distribution. In other words, we did not assume that the sensor location distributions were known. We verified the formulization using computer simulations, which showed that the analytical results and computer simulations matched exactly.

Most importantly, we proposed a distribution-free approach for estimating network coverage intensity. In our proposed method, no assumption on sensor location distribution was required. Instead, we take a small sample of the actual deployment, and carry out a statistical analysis to capture the distribution function of the deployment. In practice, this small sample could be a set of enhanced sensor nodes with GPS receivers, and thus their locations can be known. Furthermore, we used the kernel-density estimator to estimate the deployment distribution. Based on the obtained knowledge, the network coverage metrics can be calculated.

The results show that a small sample of sensor nodes yields fairly good estimates of the distribution used. In particular, compared to the case in which a different assumption (the uniform distribution) than actual sensor location distribution (GU distribution) is used, the distribution-free approach yields far better results.

Future work in this direction includes, but is not limited to: (1) minimizing the number of sample sensors while maintaining certain estimation precision; (2) proposing an in situ method to determine the number of sample sensors needed (which is empirically determined beforehand); (3) developing and evaluating a complete set of protocols that integrate sensor network location discovery, routing discovery, and distributed scheduling where network coverage is estimated using the proposed approach. Finally, though this paper only studies sensor network coverage, we believe that this methodology can be generalized and extended to study many other sensor network metrics.

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