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Improved Cuckoo Search based Sensor Deployment Scheme for Large-scale Wireless Sensor Networks

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ABSTRACT

Wireless Sensor Network (WSN) consists of small number of low-cost sensor nodes, which are able to freely converse over short distances. One of the key important problems in Wireless Sensor Networks (WSNs) is how to proficiently position sensors to cover an area. In WSN, sensor deployment is considered as one of the major important issues, since it not only considers the network cost during network model creation in addition it also affects how well a region is examined by means of sensors. In this paper address the problem of sensor deployment in Large Scale Wireless Sensor Networks to minimize the usage of number of nodes. The local incidence rate information and an investigative sensor detection ability equation individual exploit an optimization problem designed for reducing the usage of number of sensor nodes is created. By solving the difficulty of sensor deployment, an optimal sensor deployment schema is introduced in this paper for Large Scale Wireless Sensor Networks (LSWSN). An effective Improved Cuckoo Search (ICS) based sensor deployment scheme is introduced in this work for large-area WSN where the event incidence rate differs over the sensor-deployed region. Proposed ICS deployment scheme determines the optimal number of sensors designed for a typical surveillance sensor network with the purpose of must be deployed in each local region with the purpose of minimizes the total number of sensors at the same time as satisfying the overall detection probability. Simulation results demonstrated that the proposed ICS schemes are efficient in terms of the usage of number of sensors and are distributed in nature to verify their effectiveness.

Keywords: Large-scale sensor networks, event incident rate, Wireless Sensor Network (WSN) , cognitive wireless sensor networks, distributed resource allocation and Improved Cuckoo Search (ICS).

1. INTRODUCTION

Wireless Sensor Networks (WSN) is capable technology in now days because of dynamic changing of the environment to achieve information from the physical environment. It is predicted with the purpose of WSN motivation comprises of thousands sensor nodes to millions of tiny sensor nodes, by means of reduced computational and communication cost specifications. When networked simultaneously, these unattended devices are able to present high-resolution information regarding sensed phenomena. According to the definition of National Research Council report, via the use of WSN “might fine dwarf earlier milestones in the information uprising [1]. Several numbers of applications in these types of WSN are habitat; environmental monitoring, healthcare applications, ecological sensing, emergency reply and remote surveillance toward considerately pass their information throughout the network to a major location [3]. Because of these application WSN have been paying attention on extending the hardware, software, and networking architectures required to facilitate such applications [2].

In WSN, sensor deployment is considered as one of the major important issues, since it not only considers the network cost during network model creation in addition it also affects how well a region is examined by means of sensors. So the deployment of sensor nodes with specified detection performance [3] is not an easy task. Several number of sensor deployments have been investigated and developed which majorly depending on uniform sensor deployments to same environments. For example a grid-based uniform sensor deployment scheme is introduced in [4]. These grid-based uniform sensor deployment schemes position each sensor nodes to specific grid point, and also calculate the grid distance with the purpose to reduces the usage of sensor nodes while same time as assurance of detection capability.

Some of the WSN applications such as surveillance or environmental monitoring are expected toward developed their service coverage, the sensor deployment schema designed for large-scale sensor networks which have been focused more concentration [5]–[6]. Since large-scale sensor networks environments are able to vary depending on their location, consequently more well-organized deployment schema is required by means of the local environment information. In specific, known a region of interest, we say with the intention of the region is k-covered if each location in with the purpose of region be able to be monitored through at least k sensors, where k is a known parameter. A large amount of applications might inflict the constraint of $k > 1$. For example consider a military or surveillance applications by means of a stronger monitoring requirement might impose with the intention of$k>2$ toward avoids leaving uncovered holes when some sensors are broken down. Location protocols by means of triangulation need at least three sensors (i.e., $k > 3$) in the direction of identify each location where an object might appear. Furthermore, a number of strategies proposed in recent work are performed based on $k>3$ to perform information fusion and to reduce the impact of sensor failure. In adding together, to expand a WSN's lifetime, sensors are divided into k sets, each able of covering the complete area, to effort in shifts [8].

In the recent work another one work is also performed to solve gallery problem [8] with less computational complexity for geometry. It aims to make use of the less number of observers toward examine a polygon area. The difficulty presumes with the intention of an observer be able to observe very point as long as line-of-sight exists and but it doesn't focus on wireless communication problem among observers. Another important problem in WSN is how to place the base station (BS). This problem converse how to establish the optimal number and locations of BSs inside an environment consequently as to assure the coverage and throughput necessities. To conquer this problem several numbers of the methods have been proposed in literature among them some of the methods are multi-objective genetic algorithms, parallel evolutionary algorithms [9], and simulated annealing toward verify the optimal placement of BSs. On the other hand, these methods mightn't directly apply to sensor deployment placement problem.

In this paper address the problem of sensor deployment in Large Scale Wireless Sensor Networks to minimize the usage of number of nodes. The local incidence rate information and an investigative sensor detection ability equation individual exploit an optimization problem designed for reducing the usage of number of sensor nodes is created. By solving the difficulty of sensor deployment, an optimal sensor deployment schema is introduced in this paper for Large Scale Wireless Sensor Networks (LSWSN).An effective Improved Cuckoo Search (ICS) based sensor deployment scheme is introduced in this work for large-area WSN where the event incidence rate differs over the sensor-deployed region. Consequently, we are able to give several locations as starting point in the foundation and sensors determination is extended to their locations depending on the ranges specified in a distributed manner. The remaining section of the paper is summarized as follows. In Section III presents the system or network model for LSWSN and related specification for each notation will be described. And then an optimal sensor deployment algorithm followed by Improved Cuckoo Search (ICS) based is discussed in detail to discover an optimal location of the nodes for LSWSN is addressed in Section IV. In Section IV, network simulation results indicates that the proposed ICS scheme outperforms a conventional scheme is discussed in detail. Finally, conclusions and scope of future work extension will be presented in Section V.

2. RELATED WORK

There has been a several number of investigation methods have been carryout to measure the capability limit of WSN lately [9]. Most of the work majorly focuses on how to reduce the network capacity as it scales up and the decrease rate is varied for different topologies and their measurements. Taking into consideration the complexity to substitute the sensor's battery, the capability limit difficulty burdens the deployment of LSWSN. To enhance the network lifetime of LSWSN, several aspects of the issues have been extensively studied and solved those issues. In the literature [10-11] major objective is to decrease the power usage of transmitter at the same time as maintaining the network connectivity.

In [10], suggested a two distributed algorithms to the dynamically adjustment of power level to each transmitter as per-node basis. Evaluate the optimized transmit power range or level by defining the minimum transmit power level used by means of each and every one nodes necessary toward promise network connectivity. This is popular in WSN where nodes are moderately easy and it is complex to adjust the transmit power after the completion of optimal sensor deployment schema. The optimal transmit power is calculated via the use of the finding optimal routing and the use of Medium Access Control (MAC) protocols; on the other hand, the distributed algorithms is expanded to other type of routing schemas and varies types of MAC protocols as well. In deriving the optimal transmit power, differentiate distributed algorithms from a conventional graph-theoretic approach while the consideration of real physical layer distinctiveness. Since the connectivity used in this paper is measured in terms of the Quality of Service (QoS) constraint specified by means of the highest Tolerable Bit Error Rate (BER) at the end of a multihop routing by means of an average number of hops.

A novel Adaptive Transmission Power Control (ATPC) technique is introduced in [11] to each node which creates a model to all nearest nodes by measuring the correlation among transmitter power and link quality. In ATPC, make use of feedback-based transmission power to dynamically adjustment of link quality over time. The major contribution of the work which uses a pairwise transmission power control, which is considerably, varied from conventional node-level or network-level power control approaches. In addition it is also extended to link quality dynamics on various locations and above a long period of time. The simulation results from real-world examples indicates that the pairwise adjustment of the ATPC obtains less usage of energy via the fine tuning capacity and 2) by using online control in ATPC is robust even by means of environmental changes over time.

Random sampling in geometric sets schema is introduced in [12] for Large Scale Wireless Sensor Networks (LSWSN). It follows a sampling based procedure to choose how many number of senor nodes should be drawn to formulate every point in a probably unknown scene covered by means of at least one sensor. Let us consider an example of node placing of sensor network units with the intention of guarantees network coverage and connectivity with small number of nodes. For sensor deployment here there are two types of schemas is introduced. If the sensor deployment is attained for one environment then in airborne deployment how to select optimal sensor nodes becomes questionable .At the same time as the network coverage and network connectivity becomes also questionable .To solve these problems incremental deployment schema is introduced in which the algorithm dynamically adjusts the sensor deployment and necessitate only a small number of sensors.

In [13] suggested a new signal-strength-based schema to determine how well a sensing field is covered/monitored. In the initial stage of the work create a Gaussian-error model to track objects by using the single sensor node. Secondly proposes an error model for location finding to each object which is already known. These results optimal location finding point of WSN is presented. Apply these methods to various applications such as error reduction, environmental monitoring and scheduling power modes of sensor nodes demonstrated the simulation results.

In [14] introduced a Grid-Quorum model, here the sensor network model is divided into grids, and sensor nodes are moved beginning high-density grids to low-density grids to achieve further uniform coverage. Grid-Quorum model discover the motion ability to move sensors to compact with sensor failure. This model describes the problem of sensor replacement and proposes a two-phase sensor replacement schema, here in the initial stage of the work redundant sensor nodes are identified and then reposition to the target location. Proposed model solution toward rapidly locate the neighboring redundant sensor by means of low message complication, and make use of cascaded group to move the redundant sensor in a appropriate, well-organized and objective way. Simulation results demonstrated that the proposed Grid-Quorum model performs well when compared to conventional schemas in terms of relocation time, total energy consumption. The work [15] considers adding together more than a few mobile sensors addicted to a stationary sensor network toward ncrease the network coverage and connectivity of the original WSN. It can be concluded that proposed work is varied from other existing network by adding different number of sensor nodes from the sensor dispatch problem.

The work in [4] forms the sensing field by means of grids and considers two different types of sensors by means of different costs and sensing ability to be positioned in the sensing field. The aim is to create every grid point is under the k-coverage and the reduced total cost. On the other hand, both [14] and [4] mightn't address theassociationamongr_c and r_s. Some of the works in the literature address the issues of network coverage and connectivity by considering redundancy in the initial stage of the sensor deployment only and the objective is to choose a minimal set of active sensors towardattain energy consumption and preserveentire coverage of the sensing field in the network.

3. PROBLEM FORMULATION AND SYSTME MODEL

In WSN with large-scale sensor environments might be varied depending on their localities, therefore furtherwell-organized deployment is able to be introduced via the use of local environment information. From this point of view a local information support sensor deployment which makes use of region dependent sensor connectivity distances was proposed [16]. In addition sensor connectivity distances of large-scale sensor environments can be also varied depending on their localities and, event occurrence rates. So more well-organized deployment schema is required for large-scale sensor networks which are illustrated in Figure. 1.In this system model, a sensor deployment scheme through assistance of local event occasion rate information in order to exploit the overall detection ability designed for the specified number of sensors was suggested [17].

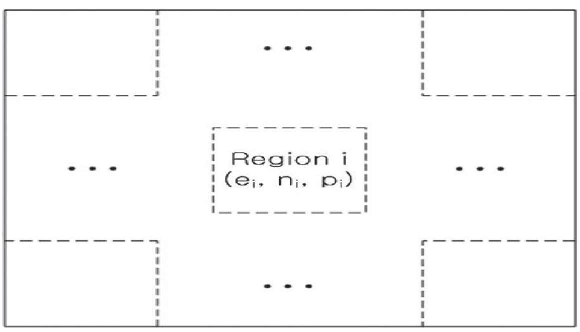

Figure. 1. System model

Furthermore it also reduces the packet loss ratio while minimization of the usage of sensor nodes via the use of condition of the specified overall detection probability relying on the local event occurrence rate at the same time as applying the sensor detection probability of (1). Finding the total number of sensor nodes in each region of large scale sensor networks becomes a one of the most important discrete problem. In this model we make an assumption by sensing range of perimeter l which is same for all sensors in the model, consequently the detection probability for region i through $n_i$sensors be able to be followed by

$$p_i = 1 - e^{-\sum_l^{n_i} \frac{l}{L}} \tag{1}$$

Let $P_{det}$is specified as the overall detection probability designed for the entire region, which is determined by

$$p_{det} = \sum_i e_i . p_i \tag{2}$$

This work introduces a simple model through a reduction of the problem is considered as the continuous problem. At initial stage of the work, the case designed for uniform deployment is evaluated, and then an optimal sensor deployment schema is applied with purpose which achieves reduction through an well-organized use of the local information is offered. In uniform deployment schema places the equal number of sensors in every sub-region. Let n_i represents the total number of sensor node within the specified region i. Then specify the condition toward meet the average required detection probability $P_{req}$is

$$\sum_i^N e_i \left(1 - e^{-\sum_l^{n_i} \frac{l}{L}}\right) \geq P_{req} \tag{3}$$

Because $\Sigma^N{}_i e_i=1$, n_i designed for the uniform deployment schema be able to be determined by

$$n_i = \frac{L}{l} \ln\left(1 - P_{req}\right) \tag{4}$$

A continuous problem or optimization problem P_o to find out the number of sensors used for each region at the same time as achieving the smallest amount total number of sensors by means of the constraint of necessary average detection probability is mathematically represented as

$$P_o : \text{Minimize}_{n_i^s} \sum_i^N n_i \tag{5}$$

$$\text{satisifes that} \sum_i^N e_i p_i \geq P_{req} \tag{6}$$

$$n_i \geq 0 \ (i = 1, .. N) \tag{7}$$

where equation (7) is considered as the major objective function used for reducing the usage of the total number of sensors deployed entire local regions, and equation (8) is a constraint with the intention of the average detection probability entire local regions might be less than or equal final objective value. $p_i$in equation (8) be able be applied with the right side of equation (2) and $\Sigma^N{}_i e_i=1$. Then, P_o is reformulated as

$$P_o : \text{Minimize}_{n_i^s} \sum_i^N n_i \tag{8}$$

$$\text{satisifes that} \sum_i^N e_i e^{-\frac{l}{L} n_i} \leq 1 - P_{req} \tag{9}$$

$$n_i \geq 0 \ (i = 1, .. N) \tag{10}$$

4. PROPOSED IMPROVED CUCKOO SEARCH BASED SENSOR DEPLOYMENT SCHEME

In this paper address the problem of sensor deployment in Large Scale Wireless Sensor Networks to minimize the usage of number of nodes. The local incidence rate information and an investigative sensor detection ability equation individual exploit an optimization problem designed for reducing the usage of number of sensor nodes is created. By solving the difficulty of sensor deployment, an optimal sensor deployment schema is introduced in this paper for Large Scale Wireless Sensor Networks (LSWSN). An effective Improved Cuckoo Search (ICS) based sensor deployment scheme is introduced in this work for large-area WSN where the event incidence rate differs over the sensor-deployed region. Consequently, be able to provide several locations as seeds in the initial stage of the work, and sensors determination is extended based on their ranges in a distributed manner.

The Cuckoo Search Algorithm (CSA) is developed by replicate together the make brood parasitic actions of the cuckoo species and the Lévy flight of definite birds a fruit flies. To explain the new CSA, three rules should be pursued: the cuckoo should put down one egg at a time and indiscriminately dump it in a nest, the nest by means of the high-quality eggs represents the explanation with the purpose of carries over to the subsequently generation, and the number of available host nest is pre-specified [18]. The CSA is carried out based on the calculated probability values in the host bird be able to either throw the cuckoo egg abandon it or reposition to an original nest, which be able to be assumed as a new random solution on a new position in a cuckoo search. The CSAbe able to generate new optimal position of sensor nodes via the calculation of Lévy distribution with random walk are drawn from a Lévy distribution. In CSA the probability values of each sensor nodes is represented as $P_a$and new locations is constructed through Lévy flights [18]. When the CSA is developed via the use of Lévy flights, it is able to be presumed with the intention of the CSA adopts the flight behavior of the animal through a probability distribution and stochastic processes. In the CSA , the eggs in the nest describes the new optimal sensor node deployment position . Because each egg represents a new sensor deployment optimal solution and produces best optimal sensor deployment node position by calculation of probability values. Thus, the general steps of CSA can be summarized in algorithm 1.

Algorithm 1: Cuckoo Search (CS)

Begin Objective function f(x),

Generate initial population of n host nests xi (i = 1, 2,...,n);

While (t <MaxGeneration) or (stop criterion) Get a cuckoo randomly by L´evy flights;

Evaluate its quality/fitness $\mathbf{f_i}$**;**

Choose a nest among n (say, j) randomly;

If (f_i>f_j) Replace j by the new solution;

End A fraction (p_a) of worse nests;

Are abandoned and new ones are built;

Keep the best solutions;

Rank the solutions and find the current best;

End while Post-process results and visualization;

End

For new optimal sensor node deployment solution is defined as (t+1) in Cuckoo$i$, and the L'evy flight is represented as follows

$$x_i^{(t+1)} = x_i^{(t)} + a \oplus Levy(\lambda) \quad (11)$$

Where α> 0: the step size in accordance by means of the investigated problem scales. Furthermore, $\alpha = O$ is frequently used for ⊕ to denotes the entry-wise multiplication. The random steps are generated during large steps by means ofL'evy distribution is represented in the following relation

$$Levy(\lambda) \sim u = t^{-\lambda} (1 < \lambda \leq 3) \quad (12)$$

The improvisation of CSA is done in several ways some of them are changing the parameters values, changing distribution values and validation of the CSA results using benchmark testing functions with known analytical solutions [18]. Some of the benchmark testing functions is the bivariate Michalewicz's, enumerated De Jong's first function, unimodal function, Shubert's bivariate function, multimodal function , Schwefel's function (multimodal), Rastrigin's, and Michalewicz's function. In [18] noted positive similarities and considerable differences among Cuckoo Search and hill-climbing with some large scale randomization. In this work ICS steps is carried out by adding three major modifications. CS is a combined to Genetic Algorithm (GA) to find optimal brood parasitic actions for sensor deployment. Second, the CSALévy flights are replaced by adding step length parameter. Third, repair illegal sensor nodes by performing genetic mutation (two point crossover) to find new optimal sensor deployment position; thus, it is applied to a wider class of optimization problems.

Algorithm 2: Improved Cuckoo Search

Step 1: Begin

Step 2: Sorting

According to value-to-weight ratio $pi/wi(i=1,2,3,\ldots,n)$ in descending order, a queue $\{s1,s2,\ldots,sn\}$of length n is formed.

Step 3: Initialization.

Set the generation counter $G = 1$;

Set probability of mutation pm=0.15.

Generate P cuckoo nests randomly X_1,Y_1 , X_2,Y_2 ,…, X_p,Y_p as the number of sensor nodes

Divide the whole population into Msensor nodes, and each sensor nodes contains N ($i.e.P/M$) cuckoos;

Calculate the fitness for each individual, ,$1\leq i\leq P$,

Determine the global optimal individual $X_{gbest},_t$ and the best individual of each sensor nodes X_{kbest},Y_{kbest} ,$1 \leq k \leq M$.

Step 4: While the stopping criterion is not satisfied

do

For i = 1 to P

$k = i$ mod$M$

Select uniform randomly $p_1\neq i$

For j=1 to D

$$X_j^1 = X_j^1 + \alpha \oplus Levy\,(\lambda)$$

If $r_1\geq 0.5$ then

$Temp$= $B_g^1+r_2\times(B_j^k - X_{p1}(j))$

Else $Temp$= $B_g^1+r_2\times(B_j^k - X_{p1}(j))$

End if

End for

If $fYtemp$>(Y_i) then

X_i=$Temp$

Else if $r_3\leq FS$ then

X_i=$L+r_4\times\ U-L$

End if

End if where r_1,r_2,r_3,r_4 ~ $U(0,1)$

Repair the illegal individuals and optimize the legal individuals by performing GTM method

End for Keep best solutions.

Rank the solutions in descending order and find the current best(Y_{best},$f(Y_{best})$)

$G = G+ 1$

Step 5: Shuffle all sensor deployment the results

Step 6: End while

Step 7: End

5. SIMULATION RESULTS

In this section presents the performance evaluation results of various sensor deployment schemas .These schemas examines the performance evaluation metrics as average event detection probability and the total number of sensors as a performance measure. The proposed ICS scheme is compared to existing Uniform Deployment Schema (UDS) and Modified Uniform Deployment Schema(MUDS).In these methods sensors are uniformly placed over the region n_i in equation (4). It is presumed that location L is specified with four or five times the value of l, and e_is region are known in earlier implementation. In the implementation work consider large-scale sensor networks, where the local event occurrence rate might appear in a different way over the regions. In order to repeat different levels calculation of variance to each local event occurrence rate, a simple probability mass function is introduced in this work for different e_i's is selected which is described by a(i− N+1/ 2)+ 1N. Note with the intention of varying a from 0 to 2 N/ (N−1) , e_i's are non-negative and monotonically enlarged by means of a .The sum and average values are maintained to 1 and 1N , correspondingly. The variance of e_i's develop into the greatest when a is 2 N/(N−1) .

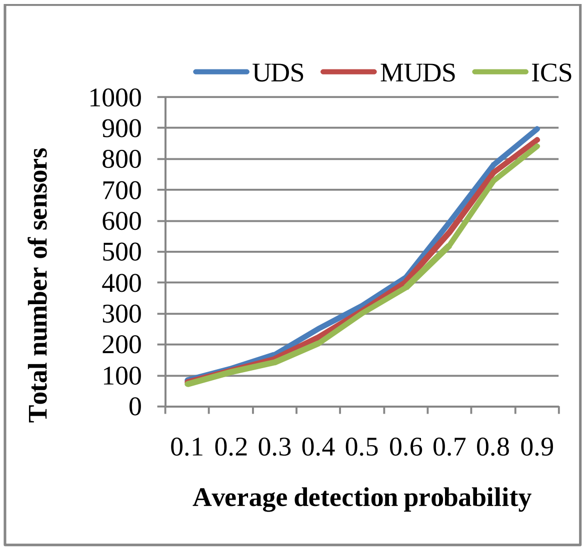

Figure. 2. Total number of sensors versus average required detection probability

Fig. 2 shows the performance accuracy results of ICS scheme is compared to existing Uniform Deployment Schema (UDS) and Modified Uniform Deployment Schema (MUDS) in terms of average detection probability .The total number of sensors designed for different values of necessary average detection probability with L value as 4. As P_{req} improves, further sensors are necessary toward assure the increased average detection probability. It have been concluded that the proposed ICS deployment achieves higher detection probability while the use of lesser or fewer sensors when compared to UDS and MUDS.

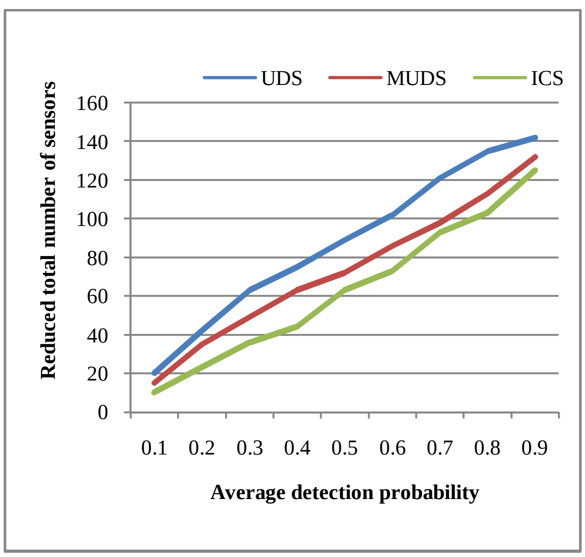

Figure. 3. Reduced total number of sensors versus average required detection probability

Fig. 3 shows the performance accuracy results of ICS scheme is compared to existing Uniform Deployment Schema (UDS) and Modified Uniform Deployment Schema (MUDS) in terms of average detection probability vs number of reduced sensors .It shows that the usage of number of sensor nodes reduced by proposed ICS schema is less when compared to UDS and MUDS methods . The gap of the number of sensors between the three deployments schemes is shown more clearly.

6. CONCLUSION AND FUTURE WORK

In WSN, sensor deployment is considered as one of the major fundamental issue for various applications. This design carry out establish types, numbers and locations of devices in order to construct a powerful and efficient system by means of devices with less energy consumption and network capacities. In this papers address the problem of sensor deployment issues related to large-scale WSN systems. An effective Improved Cuckoo Search (ICS) based sensor deployment scheme is proposed for large-area WSN here the sensor occurrence rate is varied over the sensor-deployed region. By means of utilizing the local event occurrence rate and concerning the mathematical sensor detection capability in the problem formulation .The proposed ICS scheme calculates the optimal number of sensors designed for a typical surveillance sensor network with the intention of must be deployed in each local region with the intention of reduces the usage of total number of sensors at the same time as satisfying the target overall detection probability. In future work discover and establish with the purpose of the sensing coverage provided by means of grid-based SN deployment through random errors has roughly a normal distribution. Moreover, the formulas to estimate the average and the variance of the normal distribution are consequently generic with the intention of they have been applied to a wide spectrum of deployment scenarios.

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