A Novel Swarm Intelligence Algorithm and Its Application in Solving Wireless Sensor Networks Coverage Problems

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***Abstract*—Wireless sensor networks (WSNs) have attracted a great deal of research due to their wide-range of potential applications. Sensor deployment and coverage problems are their important issues. This article briefly introduces the principle of swarm intelligence (SI). A novel SI algorithm based on information sharing of Particle Swarm Optimization (PSO) and diversity maintenance mechanism of Artificial Immune System (AIS) is designed and the model of coverage problems is given. Its applications in solving different deterministic and random coverage problems are given. The algorithm used in obtaining maximum coverage probability with given number of sensor nodes and minimum number of sensor nodes with required coverage probability of WSNs deterministic coverage, and determining the selected sensor nodes with coverage probability and connectivity requirement of WSNs random coverage, are analyzed in detail. The simulation results show the algorithm is practical. The applications of SI on K-coverage and connectivity problems in the future are also projected in the article.**

***Index Terms*—wireless sensor networks, swarm intelligence, deterministic coverage, random coverage**

I. INTRODUCTION

Wireless sensor networks (WSNs) have attracted a great deal of research due to their wide-range of potential applications. WSNs provide a new class of computer systems and expand people's ability to remotely interact with the physical world. In a broad sense, WSNs will transform the way we manage our homes, factories, and environment [1]. How well the sensors observe the physical space and how we deploy the sensors are important research topics in their applications. Traditionally there are two kinds of coverage problems: random coverage and deterministic coverage. For random sensor deployment method, the sensor location is not known a priori. This feature is required when individual sensor placement is infeasible, for example battlefield or disaster areas. If the sensors can be placed exactly where they are needed, the corresponding deployment method is deterministic. X. Wang et al.[2] studied efficient coverage area and efficient coverage area node ratio by analyzing coverage problems of WSNs. Minimum number of radio nodes required to cover a sensor field fully and seamlessly was given in his paper. However, influences of environment and sensor devices were not taken into account, and the result was based on the theoretically mathematical and geometrical analysis. J. Wang et al.[3] considered variable sensor radii and proposed a Delaunay-Triangulation-based I-coverage technique to obtain energy-efficient k-coverage. Although J. Wang went a

Manuscript received Mar. 25, 2010; revised Apr. 10, 2011.
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doi:10.4304/jnw.7.12.2037-2043

step further than X. Wang, geometric solutions are difficult to satisfy the complicated coverage requirements. The geometric solution is not flexible and it also has the disadvantages of huge calculation for multiple coverage demands. Fortunately the development of evolution computation offers great advantages[4-8]. Swarm intelligence (designed in the paper which is combined with the advantages of artificial immune system algorithm and particle swarm optimization) makes the full use of information sharing between generations and individuals.

Figure 1 is a lake for monitoring. Lots of sensor nodes are deployed in this area. What is the minimum number of nodes required to cover the field fully and seamlessly? How can we deploy the sensors if it is a deterministic sensor network? Which nodes should be awake and which should be powered off if it is a random deployment and dynamic sensor network? If the sensor nodes, just like swarm intelligence individuals, can exchange position and other individual information, these problems will become easy to be solved. In this paper we will discuss the applications of swarm intelligence in solving coverage problems considering the influence of communication radii, sensing radii, and the coverage probability of sensor nodes because of the different conditions in different sections in real environment.

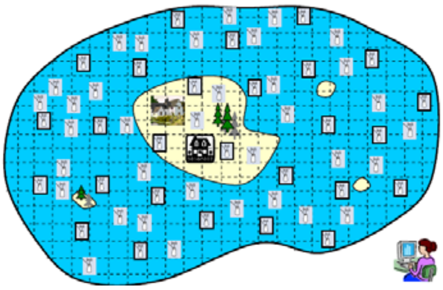


Figure 1. A lake is for monitoring

II. Principle Of Swarm Intelligence

A. *Information Sharing in Particle Swarm Optimization*

Swarm intelligence includes particle swarm optimization, ant colony optimization, and some other evolutionary algorithms. Particle swarm optimization (PSO) has become an active branch of swarm intelligence during the last decade. As a population-based technique, PSO was inspired by the emergent motion of swarms and flock behavior. Particles in PSO iteratively explore optima in a multidimensional search space by utilizing personal memories and sharing information within a specific neighborhood [9]. The swarm is typically modeled by particles with a position and a velocity, where each particle represents a candidate solution to the optimization problem. During the optimization procedure, particles communicate good positions to each other and adjust positions according to their history and the experience of neighboring particles. Due to the nature of individual memories and information sharing, particles can reach the best solution quickly. However, PSO iteration is a heuristic method and it is not able to guarantee convergence to a global optimum, but rather to a good solution or a local optimum. The basic principle of a general PSO algorithm is described by the following equations whose detail information can be seen in document [10].

$$v_{id}(n+1) = v_{id}(n) + c_1 r_1 (p_{id}(n) - x_{id}(n)) + c_2 r_2 (p_{gd}(n) - x_{id}(n)) \quad (1)$$

$$x_{id}(n+1) = x_{id}(n) + v_{id}(n+1) \quad (2)$$

The particle position $x_{id}(n)$ is updated using its current value and the newly computed velocity $v_{id}(n+1)$. By this kind of information sharing mechanism, the current optimum of the optimization function is obtained after *N* recursive computations. Since, PSO is a random heuristic method, usually the average of several *N* steps computations are required to analyze the convergence performance.

B. *Diversity Maintenance in Artificial Immune System*

As depicted above, the PSO may reach a local optimum in finding the solution. In order to make up for the shortage of PSO, we will introduce diversity maintenance mechanism from artificial immune system. Artificial immune system (AIS) is an emerging branch of evolutionary computation. It can also be seen as a kind of SI algorithm because of its antibody and antigen individuals. It encompasses unique and distinguished characteristics of pattern recognition, self-identity, data analysis, machine learning, and diversity keeping that attempt to algorithmically mimic the behavior of natural immune systems [11]. In this paper, we focus our attention on the diversity keeping mechanism of AIS.

The human immune system has two kinds of immune response: innate and acquired immune response. Once pathogens enter the body, they trigger the immune responses, especially the acquired immune response, by producing particular antibodies to match, capture and recognize pathogens (antigens). The protein chain of antibody molecules has a variable region and a constant region. The variable region can be divided into several distinct protein segments which are encoded by a group of genes. A protein segment is randomly chosen and is folded into place. The combination of random gene selection and folding results in millions of possibilities of antibody types. Together with new naturally produced antibody molecules, it is the diversity maintenance mechanism of the immune system.[12]

C. *A Novel Swarm Intelligence Algorithm*

The strategy of PSO algorithm is to optimize the fitness function by use of individual memories (the best particle of individual in all generations) and information sharing (the globe best particle with particle individuals). It can quickly reach the optimum, and is more likely to produce premature convergence and fall into a local optimal equilibrium state [13]. AIS algorithm is similar to genetic algorithm in some ways. It produces the next generation by gene mutation and molecular partial exchange. It can keep the diversity of individuals and reach the globe optimum. In the long run, however, its speed is slow. PSO algorithm and AIS algorithm both are swarm intelligence algorithms. Here we give a novel swarm intelligence algorithm combines the advantages of information sharing in PSO and the mechanism of diversity keeping in AIS. Each individual in SI can be related to a particle in PSO, and at the same time as an antibody in AIS. It produces the next generation partially as that in PSO and AIS. The detailed procedure of the algorithm is as follows:

1) Problem analysis. Identify the meaning of individuals and the fitness (optimization) function.

2) Randomly produce the first generation of swarm individuals (M).

3) Calculate the value of the fitness function, find the globe best individual, and then sequence individuals according to fitness function values.

4) Evaluate the best individual for one in all its generations.

5) Clone the globe best individual to the next generation.

6) Select the sub-best individuals (m1) and produce the same number of individuals to the next generation according to equations (1) and (2).

7) Select the sub-best individuals (m2) and produce the same number of individuals to the next generation according to gene mutation and partial molecular exchange.

8) Randomly produce some new individuals (m3) to the next generation. Individuals produced in steps 5-8 form the new next swarm generation (m1+m2+m3+1=M).

9) Repeat Steps 3) - 8) until a certain criterion is met, such as the number of generation, etc.

III. Application In Solving Deterministic Area Coverage Problems

A. Deterministic Area Coverage Problems

Although maximizing the network lifetime is the fundamental goal for WSNs design, there are still some other important objectives such as cost and quality of service, which should also be pursued and optimized in a deterministic coverage scenario. Especially, the quality of service, which is usually indicated as connectivity and the coverage probability, is very important to users. However, connectivity is related to communication radii (*Rc*) and sensing radii (*Rs*) of nodes which are usually influenced by environment. As shown in Figure 1, the islands, the forest, and the buildings will have influences on sensing radii and communication radii of the sensor nodes. How many sensor nodes should we place in the monitoring area and which positions should we place them? When connectivity is ensured, what is the maximum coverage probability with given number of sensors and what is the minimum number of sensors with required coverage probability? Zhang *et al.* [14] pointed out that the necessary condition to ensure connection in a given coverage area is $Rc \geq 2Rs$. Therefore, in the following models, *Rc* are all set as twice of *Rs* for sensor nodes.

B. The model

The coverage concept is a measure of the quality of service (QoS) of sensing function. The goal is to have each location in the physical space of interest within the sensing range of at least one sensor. Take the given monitoring area as two dimensions and use N sensor nodes with the same parameters. Suppose the position of each sensor node c_i is (x_i, y_i), ($i = 1,2,\cdots,N$); the sensing radii is *r*; the communication radii is *R* (*R*=2*r*). The set of sensor nodes are:

$$C\{c_1, c_2, \cdots c_N\} \tag{3}$$

Where $c_i = \{x_i, y_i, r, R\}$, $i = 1,2,\cdots,N$.

We will find a ‘C’ for the monitoring area, which has the minimum number of sensor nodes with required coverage probability or the maximum coverage probability with given number of sensors.

Suppose the monitoring area *A* is divided into $m \times n$ grids and the coordinates of the grid g_j are (x_j, y_j), $j = 1,2,\cdots,m \times n$. The area *A* can be denoted as

$$A\{g_1, g_2, \cdots g_{m\times n}\} \tag{4}$$

The distance between the node c_i and the grid g_j is

$$d(c_i, g_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{5}$$

Define $P\{r_{i,j}\}$ is the grid coverage probability, which is the probability that event $r_{i,j}$ will take place, that is, the probability that the grid g_j is covered by the sensor node c_i .

Due to the nature of sensing devices, obstacles and environment noise, the detection of sensor nodes shows a certain probability distribution with varying coverage radius. In practical applications, we use the following model [15]:

$$P(c_i, g_j) = \begin{cases} 1, & if \quad d(c_i, g_j) \leq r - r_e \\ e^{(-\alpha_1 \lambda_1^{\beta_1} / \lambda_2^{\beta_2} + \alpha_2)}, & if \quad r - r_e < d(c_i, g_j) < r + r_e \\ 0, & if \quad d(c_i, g_j) \geq r + r_e \end{cases} \tag{6}$$

Where $r_e (r_e < r)$ is the measure of uncertainty in detection, $\lambda_1 = r_e - r + d(c_i, p)$, $\lambda_2 = r_e + r - d(c_i, p)$; $\alpha_1, \alpha_2, \beta_1$ and β_2 are the detection probability parameters. It must be noted that the model reflects the behavior of range sensing devices and the influence of environment. The values of $\alpha_1, \alpha_2, \beta_1$ and β_2 depend upon the characteristics of various physical sensors.

In order to improve the probability of detection, the grid is usually covered by several sensor nodes. The joint probability of the grid g_j at sensor node set *C* is:

$$P_{\text{cov}}(C, g_j) = 1 - \prod_{c_i \in c} (1 - P(c_i, g_j)) \tag{7}$$

Define area coverage probability $P(A, C)$ is the probability for monitoring area A of sensor node set C [16]

$$P(A,C)=\frac{\sum P_{\text{cov}}(C,g_j)}{A}=\frac{\sum P_{\text{cov}}(C,g_j)}{m\times n\times U_A}$$
(8)

Where U_A is the area per grid, $\sum P_{\text{cov}}(C,g_j)$ is the sum of the joint probability of each grid. The following analysis and calculations are based on the above model.

C. Application and Simulation Result

1) Obtain maximum coverage probability with given number of sensor nodes

Achieving maximum coverage probability is one goal of the quality of service. To explain the application of swarm intelligence, we suppose the interested monitoring area is 1km×1km. And we want to place 10 sensors into the area to obtain the maximum coverage probability for monitoring, that is, to find the deployment positions of the 10 sensors with maximum area coverage probability. To use the SI algorithm and the model above, we divide the area into 100 grids (10×10). The area of each grid is $0.01km^2$, that is $U_A=0.01km^2=1$ Unit Area. The central coordinates of each grid are (x_j, y_j). Each individual in SI algorithm stands for a position solution for the deployment. So the dimension of each individual is 20 (10×2).

Suppose sensor node parameters:

Sensing radii: Rs=2.5; Communication radii: Rc=2Rs=5; $\alpha_1=1$; $\alpha_2=0$; $r_e=0.5Rs=1.25$; $\beta_1=1$; $\beta_2=0.5$

Select algorithm parameters:

M=50; m1=9; m2=10; m3=10; N=3000; proportion of gene-exchange in molecule: 20%.

Gene-exchange individuals are chosen from the sub-best individuals in m1 and the globe best antibody individual. So the total number of gene-exchange individuals is 10.

We conduct 3 trials. The final results of each trial for the optimization function are

Trial 1: 95.0627; Trial 2: 95.6060; Trial 3: 95.4504.

Figure 2 shows the average convergence curve of the optimization function. It can be seen that the optimization function convergences very quickly at first and becomes slow near to the optimum. The coverage probability of each trial and the sensor nodes placement coordinates (x_i, y_i) $i=1,2,\cdots,10$ in accordance with the best coverage probability and their deployment are shown in Figure 3. It shows that with deploying 10 sensors the area coverage probability can reaches more than 95% and the algorithm can practically solve coverage optimization problems with given sensors in deterministic deployment.

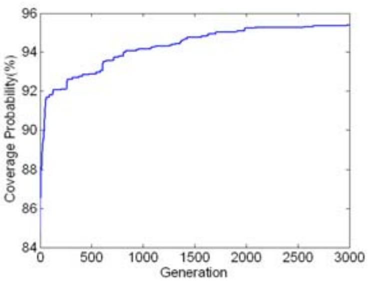


Figure 2. Area coverage optimization with SI algorithm (average of 3 trials)

2) Obtain minimum number of sensor nodes with required coverage probability

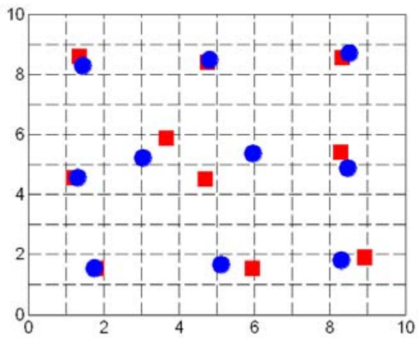
It is also a fundamental issue in deterministic wireless monitoring to find the minimum number of sensors with meeting the coverage and connectivity requirements. Suppose an area is 1Km×1Km and the area coverage probability requirement is 95%，how many sensors are needed and where they need to be installed? The SI algorithm can also be used to solve these kinds of problems, though the dimensions of individual are changeable. The area is divided into 100 grids. The sensor nodes parameters and the algorithm parameters are the same as above. The algorithm routine is as follows:

Firstly, we should give a minimum number of needed sensors according based on our prior experience. It is related to the dimension of the swarm individuals. The amount is not exact and we can choose a little less number.

Secondly, we use the SI algorithm to optimize the coverage probability with the above parameters. For each sensor, we evaluate the coverage probability 3 times. If the optimized coverage probability meets our requirement, we terminate the calculation. If we can not find the best individual meeting our coverage requirement in all the 3 trials, the number of sensors will be increased by 1.

Finally, for each added sensor we repeat the process in step 2 until we find the best individual that meets our coverage requirement. The best individual is the placement coordinates of the optimized coverage probability.

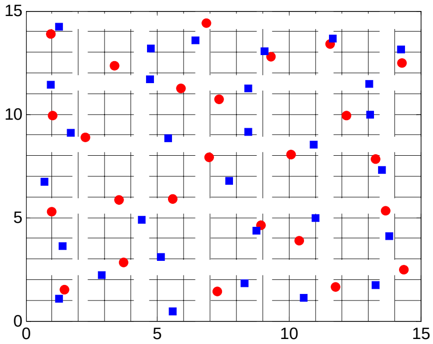
For the above problem, 10 sensors are required to meet the coverage requirement of 95% and the optimized coverage probability is 95.0304%. The simulation deployment is shown in Figure 3. In order to show the practicality of our algorithm, we changed the area to 1.5Km × 1.5Km and divide the area into 225 grids. Then we obtain minimum sensors for 95% and 98% coverage requirement which are 25 and 28 sensors and the optimized coverage probability is 95.0430% and 98.0211%, respectively. The simulation deployments for 1.5Km × 1.5Km area are shown in Figure 4. The results show that the algorithm can practically be used.



●- Positions with area coverage optimizing (sensor quantity given: 10 sensors)

■- Positions with number optimizing (coverage requirement given: 95%)

Figure 3. Sensor nodes deployment in 100 grids



●- Positions with sensor quantity optimizing and area coverage requirement of 95% (minimum sensors: 25)

■- Positions with sensor quantity optimizing and area coverage requirement of 98% (minimum sensors: 28)

Figure 4. Minimum sensor nodes deployment in 225 grids

3) Additional use explanation with special requirement

In some cases, there are some sections must be monitored in the area, for example the island section in lower left corner of Figure 1. It means we must place sensor nodes there no matter to obtain the maximum coverage probability with given number of sensors or the minimum number of sensors with required coverage probability. At the same time, it means we know the sensor node positions there a priori. Therefore, some individuals in SI for the solution are known in advance. In such circumstances, we can also use swarm intelligence to solve the two deterministic problems above. The procedure is the same except that we do not need to update these individuals during the SI algorithm processing process. Here we don't give the detailed algorithm and the simulation result for this case.

IV. Application In Solving Random Deployment Area Coverage Problems

A. Random Deployment Area Coverage Problems

As depicted above, random deployment is usually taking place when the sensor placement is infeasible. Sensors may be scattered by the airplane for a monitoring lake, forest, battle field, etc. As shown in Figure 1, some regions may have high density sensor nodes. However, it does not need all sensor nodes to join in during WSNs construction. In providing service, some nodes are awake (nodes with black edge in Figure 1) and some should be power-off (nodes without black edge in Figure 1) to prolong the lifetime of the whole net. How can we choose the sensors and what is the number of them? Do they satisfy the coverage probability and connectivity requirement? These are fundamental random deployment coverage problems.

B. The Model

Because sensor nodes have been scattered in advance, the positions information can be achieved for example by the GPS module carried by the sensor node. However it is more complex during WSNs organizing because of the high density sensors compared with the deterministic deployment for the same size monitoring area. We can also use the model described in section III except that coordinates of sensors are given. They are not variables and we can only choose them to organize the net. After getting the position information of each node, the dynamic net organizing, the SI algorithm, and the node wake and power-off control can be dealt with at the terminal PC as shown in Figure 1.

C. Application and Simulation Result

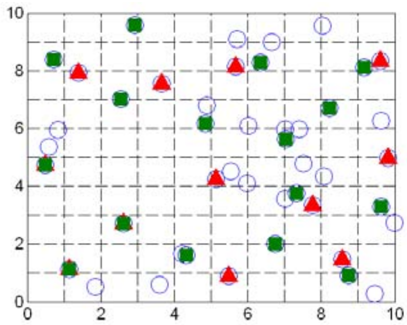
We also suppose the monitoring area is 1km×1km and divided into 100 grids(10×10). There are 45 sensor nodes are scatted in the area. We will determine how many sensors we should choose and which sensors they are with the coverage probability requirement of 95% and 98%. Sensor node parameters and algorithm parameters are the same as that in section III. Because we can only select the scattered sensors, there is no gene-exchange and no new produced individuals in the algorithm. However information sharing is still between father generations and son generations, and between the individuals in the swarm. The algorithm routine is as follows:

Firstly, give a minimum number (not exact, usually choose a little less) of needed sensors according based on our prior experience. Then, randomly select the number of sensor nodes to calculate the coverage probability with SI algorithm.

Secondly, determine whether the coverage probability satisfies our requirement or not. If yes, we figure out the selected nodes, give the deployment, stop the SI calculation and organize the net. Otherwise, if the coverage value is bigger than the previous one, we use the current swarm individuals set to replace the previous set; if not, we maintain the previous swarm individuals set.

Thirdly, we randomly select the number of sensor nodes and calculate the coverage probability again. And repeat the step 2, until finish the evolving generations of N.

Fourthly, if it is still not to satisfy the coverage probability requirement, add 1 to the minimum number of needed sensors. Repeat step 2 and step 3, until to satisfy the coverage requirement or to reach to the scattered sensor nodes number.



O- Positions of scattered sensors

▲- Selected sensors with coverage requirement of 95%

■- Selected sensors with coverage requirement of 98%

(sensor quantity: **O** 45; ▲ 12; ■ 16)

Figure 5. Simulation result of random sensor nodes deployment

The simulation results are shown in Figure 5. 'O' stands for the original scattered the sensors. '▲' and '■' are the selected sensors by SI with coverage requirement of 95% and 98%, respectively. We can see some sensor nodes are both selected by SI for coverage requirement 95% and 98%. And as shown in Table 1, there are more sensors needed to meet the same coverage requirement compared with the deterministic deployment, because to organize the net in random deployment we can only choose the limited positions of the scattered sensors.

TABLE 1
SENSOR QUANTITY NEEDED IN DETERMINISTIC AND RANDOM COVERAGE PROBLEMS

coverage requirement: 95%		coverage requirement: 98%	
deterministic deployment	random deployment	deterministic deployment	random deployment
10	12	13	16

V. CONCLUSION

In this article we briefly introduce the principle of swarm intelligence and the coverage problems of wireless sensor networks. Based on the mechanism of information sharing and diversity maintenance of swarm intelligence and the coverage model, a novel algorithm is designed and described. The applications for solving the different deterministic and random coverage problems are discussed. The simulation results for optimizing sensor amount and coverage probability in deterministic deployment and for selecting sensor nodes with coverage requirement in random deployment are given. The results show the SI is practical in solving WSNs coverage problems and more sensors are needed in random deployment than in deterministic deployment with the same coverage requirement. The comparison of the algorithm to PSO and AIS for solving coverage problems is given in another paper. In future, to explore and analyze the application of swarm intelligence on K-coverage and connectivity problems is prospected.

ACKNOWLEDGMENT

Thanks to the reviewers for the valuable comments. The work is supported by the collaborative research between University of Windsor, Guangxi University for Nationalities, and Nanchang University.

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