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A Novel Sensor Deployment Approach Using Fruit Fly Optimization Algorithm in Wireless Sensor Networks

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***Abstract*—The sensor deployment is a fundamental problem in wireless sensor networks(WSN), the performance of WSN largely depends on a good sensor deployment scheme. In this paper,we present a novel sensor deployment scheme based on fruit fly algorithm(FOA) to improve the coverage rate. Each fruit fly represents a solution for sensor deployment independently, and they are given the random direction and distance for finding food using osphresis.Then we find out the fruit fly with the highest smell concentration judgment value from the fruit fly group and keep its positions,and then the fruit fly group will fly towards that position by using their sensitive vision.We have done simulations both in the ideal and obstacle areas, FOA-based sensor deployment is compared with the classic standard PSO and the novel GSO,simulation results show the effectiveness of the proposed approach.**

Keywords*—*wireless sensor networks;sensor deployment;fruit fly optimization;obstacle

I. INTRODUCTION

Wireless sensor networks(WSN) is one of the main support technology of Internet of Things. It has broad application prospects in environmental monitoring, agricultural technology, medical care and so on [1]. Coverage problem is one of the basic problems of WSN; it mainly reflects the quality of service of the wireless sensor networks, in real situation, the initial random sensor deployment may lead to the problem of coverage hole and redundancy. Therefore, how to optimize the deployment of sensors to achieve the maximum coverage rate and small redundancy in WSN is widely discussed [2,3].

The sensor deployment can be divided into static and dynamic deployments. The static deployment may need to calculate the position in advance, and the sensor node can no longer move anymore once deployed. Different with it, dynamic deployment can automatically change sensor nodes' positions to proper positions according to the practical environment. With the improvement of sensor node design technology, dynamic deployment is widely studied in recent years [4]. In order to improve the coverage rate for dynamic deployment, swarm intelligence optimization algorithms are widely used in coverage optimization problem in WSN,for instance,particle swarm algorithm (PSO) [5-6],genetic algorithm (GA) [7], artificial immune systems (AIS) [8], glowworm swarm optimization (GSO) [9], artificial bee colony algorithm (ABC) [10,11],and so forth. Swarm intelligence algorithms are inspired from biological phenomenon in the nature and usually used to solve the optimization problem,the dynamic sensor deployment actually belongs to the optimization problem. Simulations have shown that these algorithms can improve the coverage rate of WSN and the network service performance at some certain extent.

Recently,a novel biological optimization algorithm called fruit fly optimization algorithm(FOA) is proposed by Taiwan scholar in 2011 [12].When compared with other intelligent algorithms, fruit fly optimization algorithm is simpler and have less parameters. At present,FOA and its improved algorithms have been applied in several applications,such as numerical optimization problems [13-15], neural network parameters optimization, SVM parameters optimization ,PID controller parameters optimization [16-23], multidimensional knapsack problem [24], flow shop scheduling problem [25], etc. Since FOA is proposed very late, there is few research both at home and abroad, so we need to further study the theory of FOA and expand its application in other areas. Therefore,in this paper,we try to use FOA to optimize sensor deployment in WSN firstly, and proposed a sensor deployment scheme based on fruit fly optimization algorithm to enhance the coverage rate. We choose the classic standard PSO and the novel GSO for comparison,simulation results show that FOA-based sensor deployment can provide better coverage rate and faster convergence speed.

The rest of the paper is organized as follows: Section II describes WSN coverage model. The fruit fly optimization algorithm and its application in WSN is presented in Section III. Experiment results and analysis are discussed in Section

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IV, and Section V concludes the paper.

II. WSN COVERAGE MODEL

We consider the target monitoring area A is a two-dimensional region; there are n mobile sensors deployed randomly in this area and can be expressed as $S=\{s_1,s_2,...,s_n\}$. The i-th node's location is expressed as $s_i=(x_i,y_i)(i=1,2,...,n)$, the Euclidean distance between the i-th sensor node s_i and the point p(x,y) is defined as follow:

$$d_{ip}=\sqrt{(\mathrm{x}-\mathrm{x}_i)^2+(\mathrm{y}-\mathrm{y}_i)^2} \quad (1)$$

Sensor detection model is divided into binary detection model and probabilistic detection models[18,19]. This paper adopts binary detection model for convenience. Binary detection model is defined as follow:

$$p=\begin{cases}1 & if \quad d_{ip} \quad \le \quad r\\ 0 & else\end{cases} \quad (2)$$

where r is the sensing radius, d_{ip} is the Euclidean distance.

The objective of coverage optimization is to reach maximum coverage rate while using limited sensors. The placement of sensors needs to be uniform and reasonable. Coverage rate is used to evaluate the coverage performance, and it is the objective function of WSN coverage control that need to be optimized.

We suppose the monitoring area is divided into M*N grid point, the grid point is covered with probability one once it is covered by any sensor node. The total number of the covered grid point is denoted as N_{effect} ,then we define the coverage rate as follow:

$$p=\frac{N_{effect}}{M*N} \quad (3)$$

For the convenience of discussion, we make the following assumptions: (1) every sensor node is homogeneous, the communication radius is twice the sensing radius; (2) each sensor node can get its coordinate information by GPS; (3) sensor nodes have free mobile ability and can move to the specified location exactly.

III. THE PROPOSED METHOD

A. Fruit Fly Optimization Algorithm

Fruit fly optimization algorithm(FOA) is a novel swarm intelligence algorithm for finding global optimization,which is inspired from the behavior of finding food of fruit fly group. Related studies show that fruit flies have group foraging behavior,and can share the food information.Since fruit fly is superior to other species in the sense of smell and vision,they can quickly lock the position of food source.The foraging behavior of fruit fly includes two stages: collecting the scents floating in the air by osphresis organs and getting close to the food;flying towards food's location accurately by using its sensitive vision[12].FOA have simulated the process of foraging behavior, each individual fruit fly have its own position and smell concentration judgment value, smell concentration judgment value is determined by the smell concentration judgment function, the fruit fly group continuously follow the position which has the current best smell concentration judgment value, and gradually get close to the optimal location.

According to the features of foraging behavior of fruit fly group ,FOA's main steps can be summed up as follows:

Step 1. Initialize all the parameters, including the group scale(Sizepop),the maximum iteration number(Maxgen),the fruit fly group's initial position(X_axis,Y_axis).

Step 2. For finding food , each individual fruit fly will be given the random direction and distance using osphresis.

$$\begin{cases}X_i=X\_axis+RandValue\\ Y_i=Y\_axis+RandValue\end{cases} \quad (4)$$

Step 3. Estimate the distance of food to the origin($Dist_i$), then calculate the smell concentration judgment value(S_i), S_i is the reciprocal of distance.

$$Dist_i=\sqrt{X_i^2+Y_i^2} \quad (5)$$

$$S_i=1/Dist_i \quad (6)$$

Step 4. Smell concentration judgment value (S_i) will be substituted into smell concentration judgment function(the fitness function) in order to get the smell concentration value($Smell_i$) of the fruit fly.

$$Smell_i=Function(\mathrm{S}_i) \quad (7)$$

Step 5. Find out the fruit fly which has the maximal smell concentration value from the fruit fly group.

$$[bestSmell\ bestIndex]=\max(\mathrm{Smell}) \quad (8)$$

Step 6. Retain the best smell concentration value and its coordinates, then all the fruit flies will use their sensitive vision fly towards that location.

$$Smellbest=bestSmell \quad (9)$$

$$X\_\mathrm{axis}=X(\mathrm{bestIndex}) \quad (10)$$

$$Y\_axis=Y(\mathrm{bestIndex}) \quad (11)$$

Step 7. Judge whether it is met the stop condition,if not ,repeat step2 to step5,and if the smell concentration value is higher than the previous iterative smell concentration value ,then implement step 6.

B. FOA-based Sensor Deployment in WSN

FOA actually shows that all the fruit flies will continuously gather the current global optimal location for further precise search.Since sensor deployment is the optimization problem,so applying FOA into sensor deloyment for a better distribution is feasible.However, unlike traditional FOA, here we suppose each fruit fly represents a solution for sensor deployment independently,denoted as X(i) directly, X(i) have stored location information of all the sensors, as shown in table 1.In this paper,we will directly use X(i) to calculate the smell concentration judgment value,notice that the smell concentration judgment value is the coverage rate of sensor deployment, smell concentration judgment function is the function of calculating coverage rate, as shown formula 3.In every iteration, find out the fruit fly with the best smell concentration judgment value ,and then all the fruit flies use their vision to fly towards that location.

TABLE I. SENSOR NODE CODING

x_1	y_1	x_2	y_2	......	......	x_n	y_n

Based on the above analysis,the steps of FOA-based sensor deployment is shown as follows:

Step 1. Initialize all the parameters, including the group size(Sizepop),the maximum iteration times(Maxgen),the fruit fly group's initial position(X_axis),the number of sensors(d),the step length(s).

Step 2. Give the random direction and distance for each fruit fly to search the food using osphresis,each fruit fly is conducted independently as:

$$X(\mathrm{i},:) = X\_axis + 2*\mathrm{s}*\mathrm{rand}(1, 2*\mathrm{d}) - \mathrm{s} \tag{12}$$

where i represents the i-th fruit fly, d represents the number of sensors,s represents the search step length;

Step 3. Calculate and keep the smell concentration judgment values(or called coverage rate) of fruit fly group according to the smell concentration judgment function.

$$Smell(\mathrm{i}) = \mathrm{computecover}(\mathrm{X}(\mathrm{i},:)) \tag{13}$$

Step 4. Find out the fruit fly with the highest smell concentration value from the fruit fly group,and keep the best smell concentration value and its postion.

$$\left[bestSmell\ bestIndex\right] = \max(\mathrm{Smell}) \tag{14}$$

Step 5. Determine whether the best smell concentration value is greater than the last time, if so, update the Smellbest and then fruit fly group will fly towards the location by using their sensitive vision,if not,then go to step 6.

$$Smellbest = bestSmell \tag{15}$$

$$X\_axis = X(\mathrm{bestIndex},:) \tag{16}$$

Step 6. Enter the iterative optimization to repeat the step2-5 until meet the termination conditions.

IV. SIMULATIONS

In order to verify the effectiveness of the FOA-based sensor deployment, two parts of simulation experiments are carried out on an Intel Core i5-3230M CPU (2.6GHz) computer using MATLAB R2012a.The first part is conducted in an ideal environment without obstacle, the second part has considered obstacles in the deployment area.In this paper,we choose the classic standard PSO and the novel GSO in sensor deployment for comparison.

The experiment parameters are set as follows: the deployment area is 50x50m^2, the grid point is set to 0.4*0.4,the step length is s=0.3,the fruit fly group size is set to 20,the max iteration number is 500, the sensing radius is r_s=5. PSO and GSO's parameters are set as the literature[6][9].

A. Simulations in the ideal environment

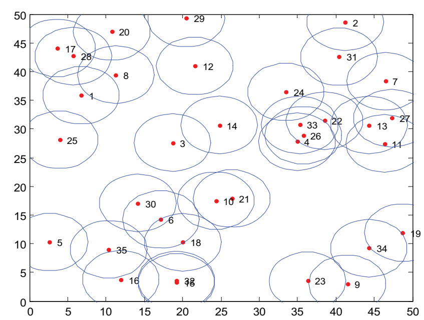
Firstly,we suppose there are 35 sensors in this area,in order to observe the performance of algorithms and overcome the randomness,each algorithm is run 15 times ,respectively.The mean coverage rate,along with the standard deviation(SD) and the best and worst coverage,are shown in the following table.

TABLE II. DEPLOYMENT RESULTS UNDER DIFFERENT ALGORITHMS

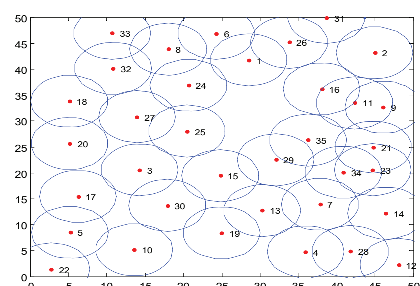
	Initial	PSO	GSO	FOA
Mean	0.7004	0.8193	0.7915	0.9199
SD	0.0002	0.0417	0.0419	0.0087
Best	0.7263	0.8782	0.8504	0.9321
Worst	0.6870	0.7217	0.7237	0.9002

We can see that FOA-based sensor deployment has achieved the average coverage about 91.99%, compared with the 82.33% of the standard PSO and 79.94% of GSO. Besides,it is obviously seen from table 2 that FOA is more stable,as the standard deviation is the smallest.

Then, in order to further highlight the performance of FOA-based sensor deployment vividly,with the same initial distribution randomly,we present the figures of sensor deployment and coverage rate curves under three kinds of algorithms.The experimental results are shown as below.



(a)



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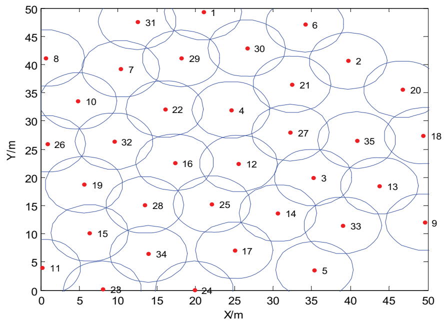
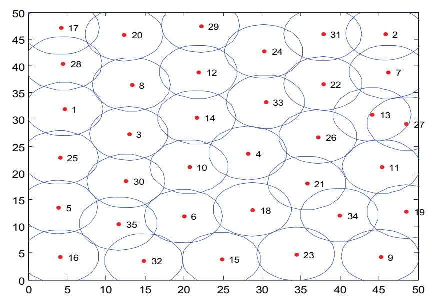


(c)



(d)

Fig. 1. (a) Initial sensor deployment. (b) Sensor deployment by PSO . (c) Sensor deployment by GSO .(d) Sensor deployment by FOA.

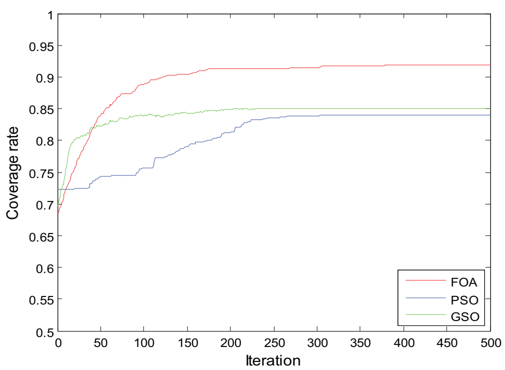


Fig. 2. Coverage rate curve by PSO, GSO,FOA

Fig.1(a) is the initial sensor deployment. Fig.1(b) and(c) are the final sensor deployment diagrams after executing PSO and GSO,respectively. Fig.1(d) is the final sensor deployment by executing FOA, it can be obviously seen that FOA-based sensor deployment is the most uniform and has the smallest redundancy. In addition, Fig.2 demonstrates that FOA have faster convergence speed and much higher coverage rate compared with the standard PSO and GSO.

Finally, in order to further verify the performance of FOA-based sensor deployment, we have done several simulations for varying number of sensors when d is equal to 10,15,20,25,30,35,40,45,respectively.and the three different algorithms in every situation will be run 20 times independently,then we can get their average coverage rates for comparison,as shown in Fig.3. It can be easily seen from Fig.3, FOA always gets greater coverage rate than the standard PSO and GSO when the number of sensors is the same. Besides,Its advantage is much more obvious, especially when the number of sensors is more than 20. These experiments strongly show the effectiveness of the FOA-based sensor deployment in this paper. At the same time, we can also see that PSO has its advantages when sensors are less,and GSO have its advantages when sensors are more.

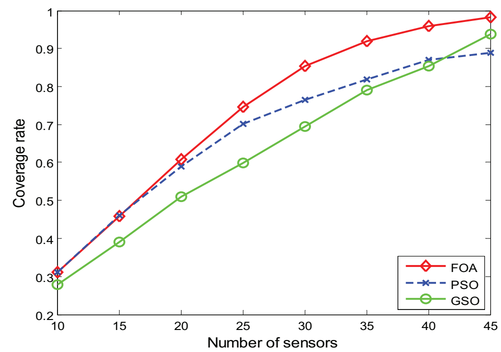
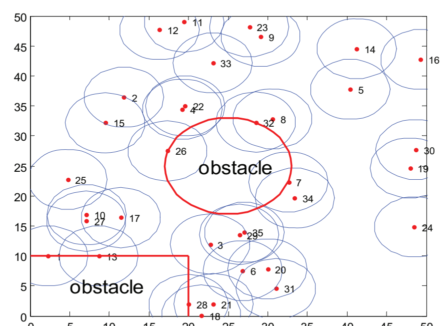


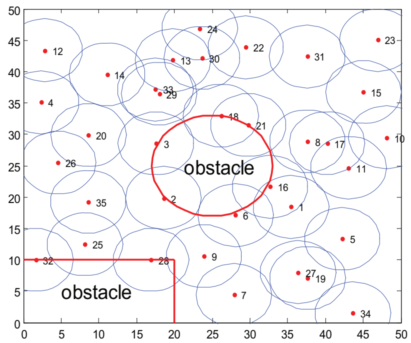
Fig. 3. Coverage rate for varying number of sensors

B. Simulations in the Room with Obstacles

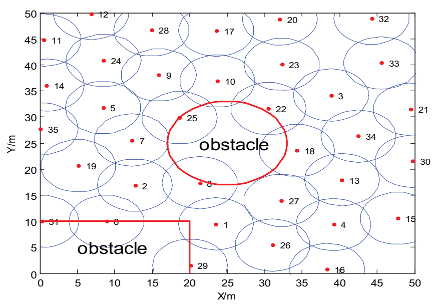
The actual deployment area may have obstacles, then the sensors can't reach or go through the obstacle areas. In order to verify the performance of FOA-based sensor deployment with obstacles, then we assume there is a circular obstacle in the middle of the deployment area and a rectangular obstacle next to the edge. All the other experimental parameters are exactly the same as the before. Firstly,we suppose there are 35 sensors to be placed in this area,and the radius of circular obstacle is 8, the rectangular obstacle is 10X20. The experimental results are shown as follows.



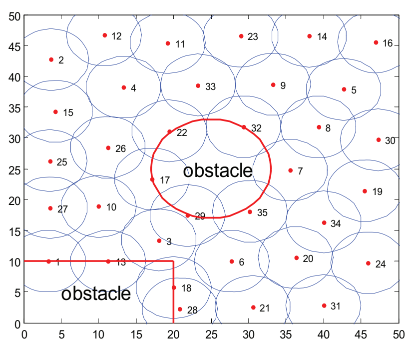
(a)



(b)



(c)



(d)

Fig. 4. Sensor deployment in the case of two obstacles:(a) Initial sensor deployment. (b) Sensor deployment by PSO (c) Sensor deployment by GSO (d)Sensor deployment by FOA

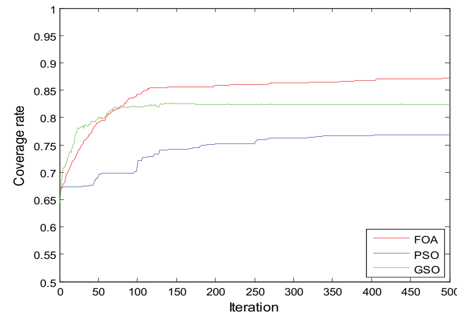


Fig. 5. Coverage rate curve in the case of obstacles

The areas surrounded by red lines in Figure 4 are the obstacle areas that sensors can't reach. Figure 4(a) is the initial sensor deployment, Figure 4(b) and (c) are the final sensor deployment after executing PSO and GSO. Figure 4(d) is the final FOA-based sensor deployment ,and Figure 5 is the coverage rate comparison in the case of two obstacles among the three different algorithms. It can be seen that FOA can still achieve higher coverage rate and faster convergence speed even if in the case with obstacles.

At the same time,we also test the performance of the proposed approach under different numbers of sensors in the case of obstacles, all the experiment parameters are the same as in section 4.1,every situation also need to be run 5 times independently, and the average coverage rate is calculated for comparison. From Fig.6 we can clearly see that experiments once again show that even if the number of sensors is different, even if there are two obstacles in the deployment area,the FOA-based sensor deployment can achieve higher coverage rate and faster convergence speed.

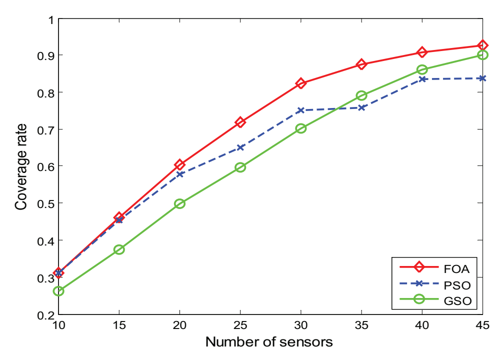


Fig. 6. Coverage rate comparison for varying number of sensors with obstacles

V. Conclusions

In order to improve the coverage rate for sensor deployment in WSN, this paper bravely propose a new sensor deployment approach based on fruit fly algorithm. FOA-based sensor deployment actually demonstrates that all the fruit flies continuously gather the current global optimal location for further precise search to obtain the optimal sensor deployment.This paper's simulations contains the ideal environment and the obstacle environment, and we have also tested the performance of the proposed approach under the condition of different numbers of sensors.When compared with standard PSO and GSO, the experimental results show that the FOA-based sensor deployment alwalys has faster convergence speed and higher coverage rate.Therefore,the proposed approach can be well applied to sensor deployment in WSN. We will discuss the influence of search step length and how to increase the diversity of the fruit fly group in the future.

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