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A Sink Node Allocation Scheme in Wireless Sensor Networks Using Suppression Particle Swarm Optimization

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1. Introduction

A wireless sensor network, which is a key network to facilitate ubiquitous information environments, has attracted a significant amount of interest from many researchers (Akyildiz et al., 2002). A wireless sensor network has a wide range of applications, such as natural environmental monitoring, environmental control in residential spaces or plants, object tracking, and precision agriculture. In a general wireless sensor network, hundreds or thousands of micro sensor nodes, which are generally compact and inexpensive, are placed in a large scale observation area and sensing data of each node is gathered to a sink node by inter-node wireless multi-hop communication. Each sensor node consists of a sensing function to measure the status (temperature, humidity, motion, etc.) of an observation point or object, a limited function on information processing, and a simplified wireless communication function, and generally operates on a resource of a limited power-supply capacity such as a battery. Therefore, a data gathering scheme and/or a routing protocol capable of meeting the following requirements has been mainly studied to prolong the lifetime of a wireless sensor network.

1. Efficiency of data gathering
2. Balance on communication load among sensor nodes

As the scheme that satisfy the above two requirements, gradient-based routing protocol has attracted attention (Xia et al., 2004). However, this does not positively ease the communication load concentration to sensor nodes around a sink node that is the source of problems on the long-term operation of a wireless sensor network. In a large scale and dense wireless sensor network, the communication load is generally concentrated on sensor nodes around a sink node during the operation process. In case sensor nodes are not placed evenly in a large scale observation area, the communication load is concentrated on sensor nodes placed in an area of low node-density. Intensive data transmission to specific nodes, such as sensor nodes around a sink node and sensor nodes placed in an area of low node-density, brings on concentrated energy consumption of them and causes them to break away from the network early. This makes the long-term observation by a wireless sensor network difficult. To solve this communication load concentration problem, a data gathering scheme for a wireless sensor network with multiple sinks has been proposed (Dubois-Ferriere et al., 2004; Oyman & Ersoy,

2004). Each sensor node, in this scheme, sends sensing data to the nearest sink node. In comparison with the case of a one-sink wireless sensor network, the communication load of sensor nodes around a sink node is reduced. In the existing studies, however, the effective locations for sink nodes, which are an important design problem for the long-term operation of a wireless sensor network, have not been discussed.

This chapter discusses a method of suppressing the communication load on sensor nodes by effectively placing a limited number of sink nodes in an observation area. As a technique of solving effective locations for sink nodes, this chapter presents a new search algorithm named the suppression particle swarm optimization algorithm (Yoshimura et al., 2009). This algorithm is based on the particle swarm optimization algorithm (Kennedy & Eberhart, 1995) that is one of the swarm intelligence algorithms. The suppression particle swarm optimization algorithm can provide plural effective allocation sets for sink nodes so that total hops in all sensor nodes are minimized. As their allocation sets are switched dynamically, the above two requirements can be satisfied.

This chapter consists of five sections. In Section 2, the basic particle swarm optimization algorithm is introduced. In Section 3, the suppression particle swarm optimization algorithm is explained. In Section 4, simulation results for two types of wireless sensor networks are presented. Through numerical simulations, effectiveness by using the suppression particle swarm optimization algorithm is confirmed. In Section 5, the overall conclusions of this work are given and future problems are discussed.

2. The Particle Swarm Optimization Algorithm

In this section, the original particle swarm optimization algorithm is outlined. The particle swarm optimization algorithm belongs to the category of swarm intelligence algorithms. It was developed and first introduced as a stochastic optimization algorithm (Kennedy & Eberhart, 1995). Currently, the particle swarm optimization algorithm is intensively researched because it is superior to the other algorithms on many difficult optimization problems. The ideas that underlie the particle swarm optimization algorithm are inspired not by the evolutionary mechanisms encountered in natural selection, but rather by the social behavior of flocking organisms, such as swarms of birds and fish schools. The particle swarm optimization algorithm is a population-based algorithm that exploits a population of individuals to probe promising regions of the search space. In this context, the population is called a *swarm* and the individuals are called *particles*. In the particle swarm optimization algorithm, a multi-dimensional solution space by sharing information between a swarm of particles is efficiently searched. The algorithm is simple and allows unconditional application to various optimization problems.

Assume a D -dimensional search space and a swarm consisting of N particles. Each particle (The i th particle) has a position vector

$$\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{iD})^T, \quad (1)$$

and the velocity vector

$$\mathbf{v}_i = (v_{i1}, v_{i2}, \dots, v_{iD})^T, \quad (2)$$

where the subscript i ($i = 1, \dots, N$) represents the particle's index. In addition, each particle retains the best position vector \mathbf{pbest}_i found by the particle in the search process and the best position vector \mathbf{gbest} among all particles as information shared in the swarm in the search

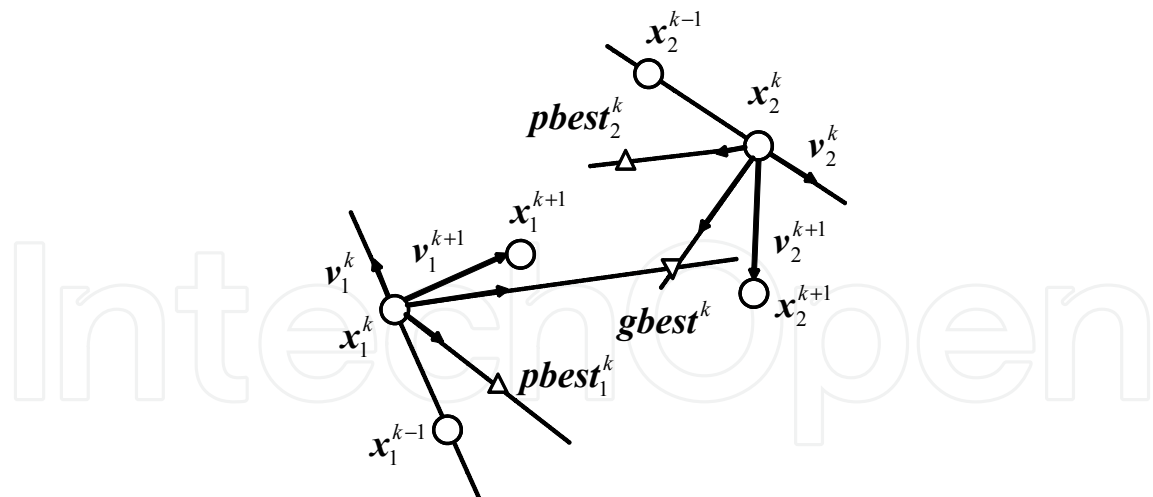


Fig. 1. The movement of particles.

process. In the particle swarm optimization algorithm, each particle produces a new velocity vector v_i^{k+1} by linearly coupling $pbest_i^k$ found by the particle in the past, $gbest^k$ shared in the swarm, and the previous velocity vector v_i^k and moves to the next position x_i^{k+1} , where the superscript k indicates the number of search iterations. At the $k + 1$ th iteration, the velocity vector v_i^{k+1} and the position vector x_i^{k+1} of the i th particle is updated by the following equations:

$$v_i^{k+1} = w \cdot v_i^k + c_1 \cdot r_1 \cdot (pbest_i^k - x_i^k) + c_2 \cdot r_2 \cdot (gbest^k - x_i^k) \quad (3)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (4)$$

where r_1 and r_2 represent random numbers, uniformly distributed within the interval $[0,1]$. w is a parameter called the inertia weight. c_1 and c_2 are positive constants, referred to as cognitive and social parameters, respectively. The settings of w , c_1 , and c_2 affect the performance of the particle swarm optimization algorithm. In Fig. 1, an example on the movement of particles is shown. By iterating the search based on Equations (3) and (4) until the end condition is satisfied, a solution to an objective function $f(x)$ can be obtained. The particle swarm optimization algorithm to search the minimization of an objective function $f(x)$ is as follows (see Fig. 2):

Step 0 : Preparation

Set the total number of particles N , the particle parameters (w, c_1, c_2) , and the maximum number of iterations K_{max} .

Step 1 : Initialization

Set the search iteration counter to $k = 1$. Generate the initial velocity vector v_i^1 and the initial position vector x_i^1 of each particle from random numbers and determine the initial $pbest_i^1$ and $gbest^1$.

$$pbest_i^1 = x_i^1, \quad i = 1, \dots, N \quad (5)$$

$$i_g = \arg \min_i f(pbest_i^1) \quad (6)$$

$$gbest^1 = pbest_{i_g}^1 \quad (7)$$

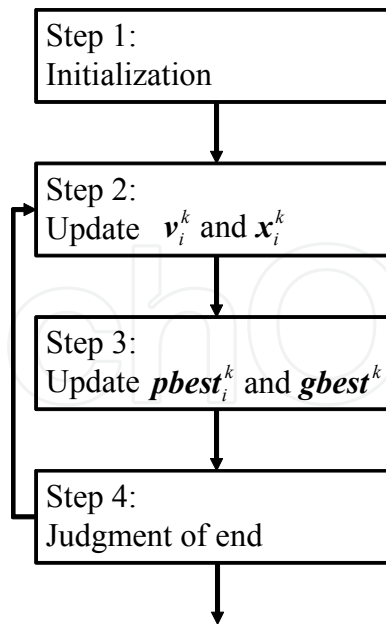


Fig. 2. Flowchart of the particle swarm optimization algorithm.

Step 2 : Update of velocity vector and position vector

Update the velocity vector and the position vector of each particle by Equations (3) and (4).

Step 3 : Update of $pbest$ and $gbest$

Update $pbest_i^{k+1}$ and $gbest^{k+1}$ as follows:

$$I_1 = \{i \mid f(x_i^{k+1}) < f(pbest_i^k), 1 \leq i \leq N\} \quad (8)$$

$$pbest_i^{k+1} = \begin{cases} x_i^{k+1}, & i \in I_1 \\ pbest_i^k, & i \notin I_1 \end{cases} \quad (9)$$

$$i_g = \arg \min_i f(pbest_i^{k+1}) \quad (10)$$

$$gbest^{k+1} = pbest_{i_g}^{k+1} \quad (11)$$

Step 4 : Judgment of end

Finish the search when $k = K_{max}$. Otherwise, return to Step 2 by assuming $k = k + 1$.

The particle swarm optimization algorithm can fast solve various optimization problems in nonlinear continuous functions, although the algorithm uses only simple and fundamental arithmetic operations. However, the basic particle swarm optimization algorithm can find only a single solution for a single trial.

3. The Suppression Particle Swarm Optimization Algorithm

In this section, the suppression particle swarm optimization algorithm having a simple self control mechanism is explained (Yoshimura et al., 2009). The overall processing flow of the suppression particle swarm optimization algorithm is shown in Fig. 3. As shown in the figure,

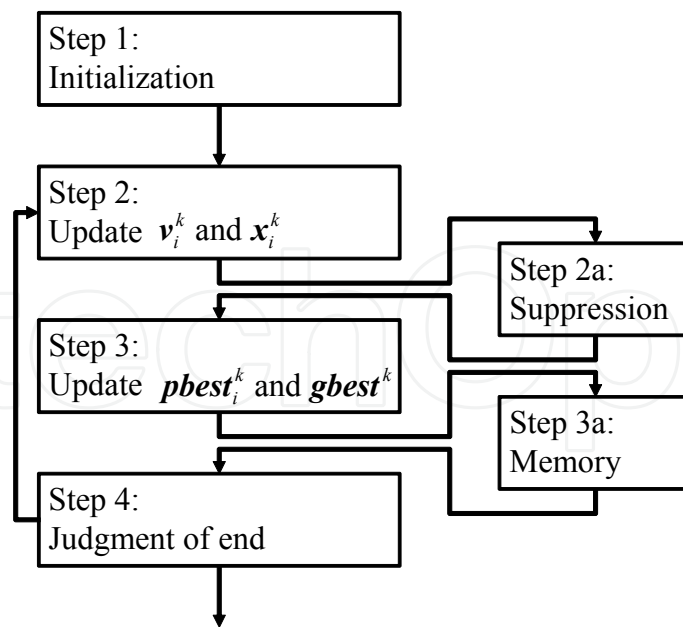


Fig. 3. Flowchart of the suppression particle swarm optimization algorithm.

“suppression” and “memory” are added to the flow of the original particle swarm optimization algorithm. The suppression scheme controls excessive conversion of particles as referring to density of particles. The memory scheme stores copies of position vectors having better evaluation values, which are distant from each other. These schemes can realize to provide various acceptable solutions.

In the suppression particle swarm optimization algorithm, distance between the i th and the j th particles is calculated by

$$distance_{ij} = ||\mathbf{x}_i - \mathbf{x}_j|| \quad (12)$$

Also, density of the i th particle is calculated by

$$density_i = \frac{1}{N} \sum_{j=1, j \neq i}^N \alpha(distance_{ij}; T_d) \quad (13)$$

where N is the number of particles, T_d is a distance threshold parameter, and $\alpha(z; T)$ is the following function.

$$\alpha(z; T) = \begin{cases} 1, & z \leq T \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

That is, the number of particles having shorter distances than the threshold T_d is proportional to the density. Let $\tilde{\mathbf{x}}_j^k$ be the j th position vector preserved in the memory scheme at the k th iteration. Set the number of the preserved position vectors to $L = 0$ in Step 1. Additional schemes in the suppression particle swarm optimization algorithm are as follows:

Step 2a: Suppression

Consider the following subset:

$$I_2 = \{i \mid density_i > T_s, 1 \leq i \leq N\} \quad (15)$$

where T_s is a density threshold parameter. Reset the velocity vector v_i^k and the position vector x_i^k to random values if $i \in I_2$ is satisfied.

Step 3a: Memory

Set the position vector x_i^k as a candidate preserved in the memory scheme if the following condition is satisfied:

$$f(x_i^k) < T_{mf} \quad (16)$$

where T_{mf} is a fitness threshold parameter. Store the candidate position vector x_i^k in the memory scheme and let $L = L + 1$ if the following condition is satisfied:

$$\bigwedge_{j=1}^L \left(\|x_i^k - \tilde{x}_j^k\| > T_d \right) \quad (17)$$

where T_d is the distance threshold parameter explained before. Otherwise, consider the following subset:

$$I_3 = \left\{ j \mid \|x_i^k - \tilde{x}_j^k\| \leq T_d \right\} \quad (18)$$

Replace the preserved position vectors \tilde{x}_j^k ($j \in I_3$) with the candidate position vector x_i^k and let $L = L - |I_3|$ if the following condition is satisfied:

$$\bigwedge_{j \in I_3} \left(f(x_i^k) < f(\tilde{x}_j^k) \right) \quad (19)$$

The suppression particle swarm optimization algorithm is based on the artificial immune system which is one of optimization algorithms (de Castro & Timmis, 2002). The living body has a mechanism to reconstruct own genes and generate antibodies which eliminate antigens from outside. The antibodies affect not only antigens but also antibodies themselves. Repeating in such a process between antibodies and antigens, effective antibodies are generated. The artificial immune system mimics such a process. This algorithm can keep a diversity of solutions by a production mechanism of antibodies and a self-control mechanism in an immunity system, and can search plural acceptable solutions. However, the artificial immune system requires large computation costs. The suppression particle swarm optimization algorithm can be regarded as a fusion algorithm which has simple and fast search functions in the particle swarm optimization algorithm, and plural solution search functions in the artificial immune system.

Purpose of this study is to suppress the communication load on sensor nodes by effectively placing a limited number of sink nodes in an observation area. However, the communication load is concentrated on sensor nodes around a sink node during the operation process of wireless sensor networks and causes them to break away from the network early. Therefore, it is needed to find plural allocation sets for sink nodes so that total hops in all sensor nodes are minimized, and to switch their allocation sets dynamically considered energy consumption of each sensor node. The suppression particle swarm optimization algorithm can provide plural effective allocation sets for sink nodes, such that the communication load of each sensor node can be reduced.

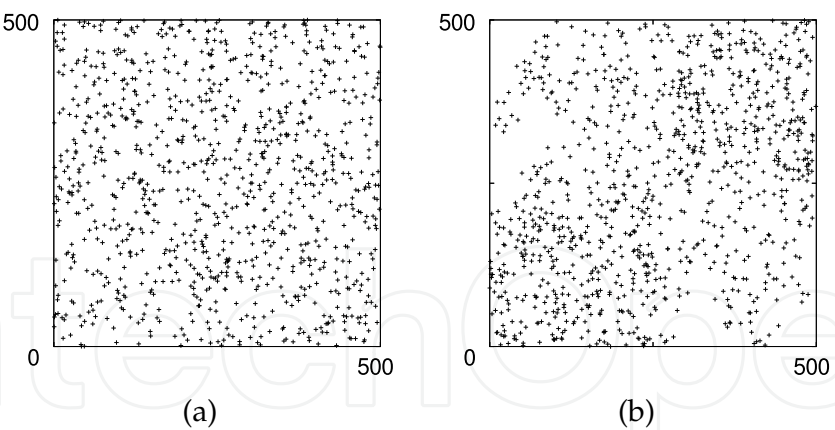


Fig. 4. Sensor node allocations. (a) Uniform node-density. (b) Nonuniform node-density.

| | | | | | | | | | | |
|------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| sink nodes | S_{i1} | | S_{i2} | | S_{i3} | | S_{i4} | | S_{i5} | |
| particle | X_{i1} | Y_{i1} | X_{i2} | Y_{i2} | X_{i3} | Y_{i3} | X_{i4} | Y_{i4} | X_{i5} | Y_{i5} |

Fig. 5. Coding method to each particle ($M = 5$).

4. Simulation Experiments

In this section, three methods, the suppression particle swarm optimization algorithm, the particle swarm optimization algorithm and the artificial immune system, are applied to a sink node allocation problem, and the solving performances are compared.

4.1 Sink Node Allocation Problem

The problem to allocate M sink nodes in a two dimensional observation area is considered. In the observation area, sensor nodes are allocated randomly as the followings:

- 1. Uniform node-density as shown in Fig. 4(a); sensor nodes are allocated evenly in whole of the area.
- 2. Nonuniform node-density as shown in Fig. 4(b); many sensor nodes are allocated in the lower left and upper right area, and few sensor nodes are allocated in the other area.

Sink nodes can be allocated at the arbitrary locations in the area. For the locations of M sink nodes in the two dimensional area, the expressions of each particle are $2M$ design variables as shown in Fig. 5. In the figure, S_{im} denotes a two dimensional location of the m th sink node which the i th particle has. In order to apply each method to this problem, $distance_{ij}$ in Equation (12) is defined as the minimum value in all Euclidean distances between sink node locations which each particle has (see Fig. 6):

$$distance_{ij} = \min_{m,n} |S_{im} - S_{jn}|, \quad 1 \leq m \leq M, 1 \leq n \leq M$$

(20)

where M is the number of sink nodes. Then, the density basically increases when at least two sink nodes which each particle has are contiguous. The evaluation value (fitness) of each particle is given by total hop counts from all sensor nodes to each nearest sink node. This fitness is used for all the methods, the suppression particle swarm optimization algorithm, the particle swarm optimization algorithm and the artificial immune system.

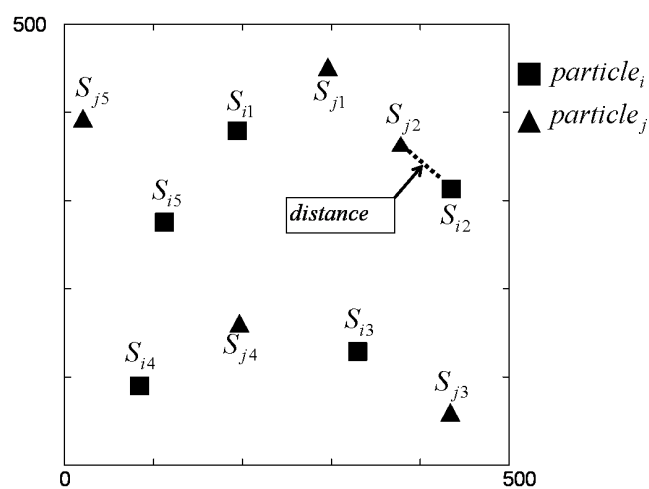


Fig. 6. Definition of distance between each particle ($M = 5$).

| Parameter | Value |
|--------------------------|------------------|
| Area Size [m^2] | 500×500 |
| Number of sink nodes M | 5 |
| Number of sensor nodes | 1000 |
| Radio range [m] | 25 |

Table 1. Conditions in wireless sensor networks.

The conditions in wireless sensor networks are shown in Table 1, and the parameters in each method are shown in Table 2, which are decided by preliminary experiments.

4.2 Average Delivery Ratio

In sink node allocation sets provided with each method, lifetime of wireless sensor networks is evaluated. Each sensor node periodically transmits sensor information to the nearest sink node. Then, the sensor node and relative relay sensor nodes consume energy (Heinzelman et al., 2000):

$$E_{Rx}(b) = E_{elec} \times b$$

(21)

$$E_{Tx}(b,d) = E_{elec} \times b + \epsilon_{amp} \times b \times d^2$$

(22)

| Parameter | Value |
|--------------------------------------|-------|
| Inertia coefficient w | 0.9 |
| Weight coefficient c_1 | 1.0 |
| Weight coefficient c_2 | 1.0 |
| Threshold of distance T_d | 30 |
| Threshold of density T_s | 0.9 |
| Threshold of fitness T_{mf} | 6250 |
| Number of particles N | 30 |
| Total number of iterations K_{max} | 100 |

Table 2. Parameters in each method.

| Parameter | Value |
|--|-------|
| Battery capacity [J] | 0.5 |
| Processing coefficient E_{elec} [nJ/bit] | 50 |
| Transmission coefficient ϵ_{amp} [pJ/bit/m ²] | 100 |
| Data size b [Byte] | 12 |
| Transmission output d [m] | 25 |
| Number of transmissions | 900 |
| Number of trials | 100 |

Table 3. Conditions in calculating average delivery ratio.

| Algorithm | SPSO | AIS | PSO |
|---------------------|------|------|------|
| Best fitness | 5274 | 5429 | 5149 |
| Average fitness | 5501 | 5701 | 5382 |
| Number of solutions | 3.73 | 3.44 | 1 |

Table 4. Fitness and the number of solutions for a uniform node-density wireless sensor network. SPSO: the suppression particle swarm optimization. AIS: the artificial immune system. PSO: the particle swarm optimization.

where E_{Rx} and E_{Tx} denote energy consumption in reception and transmission, respectively. b is data size of sensing data. d is transmission output. E_{elec} and ϵ_{amp} are processing and transmission coefficients, respectively. All sensor nodes have the same battery capacity at first, and simultaneously transmit sensing data with the same data size to each nearest sink node via some relay sensor nodes. The relay sensor nodes are selected so that each sensing data is transmitted in minimum hop counts to each nearest sink node. If plural candidates of the relay sensor nodes exist, one of them is selected randomly. If battery shutoff occurs in a relay sensor node, the sensor node can not relay sensing data. In such a situation, average delivery ratio for wireless sensor networks is calculated. Table 3 shows conditions in calculating the average delivery ratio.

4.3 Results for a Wireless Sensor Network with uniform node-density

First, simulation results for the wireless sensor network with uniform node-density shown in Fig. 4(a) are presented. Fig. 7 shows transitions of the best fitness (total hop counts) in each method. In the figure, each value corresponds to the best fitness in all particles in each iteration. Table 4 shows the best fitness, the average fitness, and the average number of the solutions preserved in the memory scheme. These are the average values for 100 trials. In the suppression particle swarm optimization algorithm and the artificial immune system, it is possible to search widely in the solution space by the self-control mechanism and each fitness does not converge monotonously. On the other hand, in the particle swarm optimization algorithm, fitness converges to a single solution and it is not possible to search other solutions. As comparing quality of solutions, the particle swarm optimization algorithm is the best in all the methods. However, it should be noted that the suppression particle swarm optimization algorithm and the artificial immune system can search plural acceptable solutions while the particle swarm optimization algorithm can not. Fig. 8 shows three allocation sets for five sink nodes finally obtained by the suppression particle swarm optimization algorithm. As shown in the figure, all the sink nodes are allocated without overlapping. This is very important in

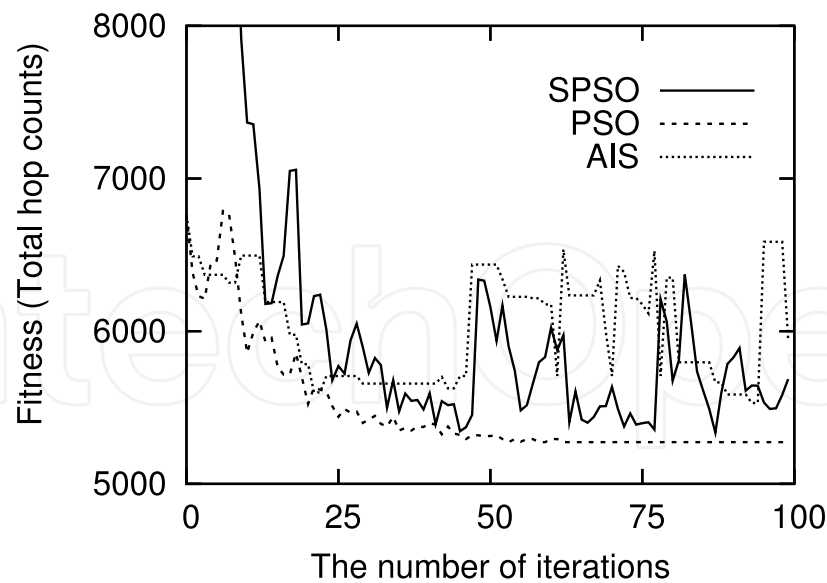


Fig. 7. Fitness in each method for a wireless sensor network with uniform node-density. SPSO: the suppression particle swarm optimization. AIS: the artificial immune system. PSO: the particle swarm optimization.

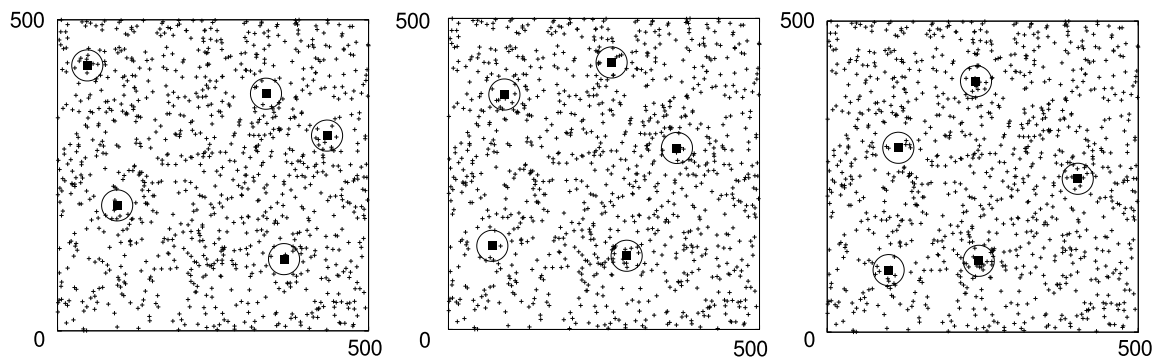


Fig. 8. Three allocation sets for five sink nodes in a uniform node-density wireless sensor network obtained by the suppression particle swarm optimization algorithm.

the viewpoints of suppressing communication load in each sensor node. Fig. 9 shows average delivery ratio for the following three methods:

SPSO: Three sink node allocation sets obtained by the suppression particle swarm optimization algorithm are switched in every 300 transmission.

PSO: The best sink node allocation set obtained by the particle swarm optimization algorithm continues to be used during 900 transmissions.

Regular: The regular sink node allocation set in the area continues to be used during 900 transmissions.

Sink node allocation sets obtained by all the methods are shown in Fig. 10.

It is found that average delivery ratio in the suppression particle swarm optimization method is higher than those in the particle swarm optimization method and the regular allocation method. Because, communication load in each sensor node is distributed by dynamically switching sink node allocation sets. That is, energy consumption of sensor nodes is balanced.

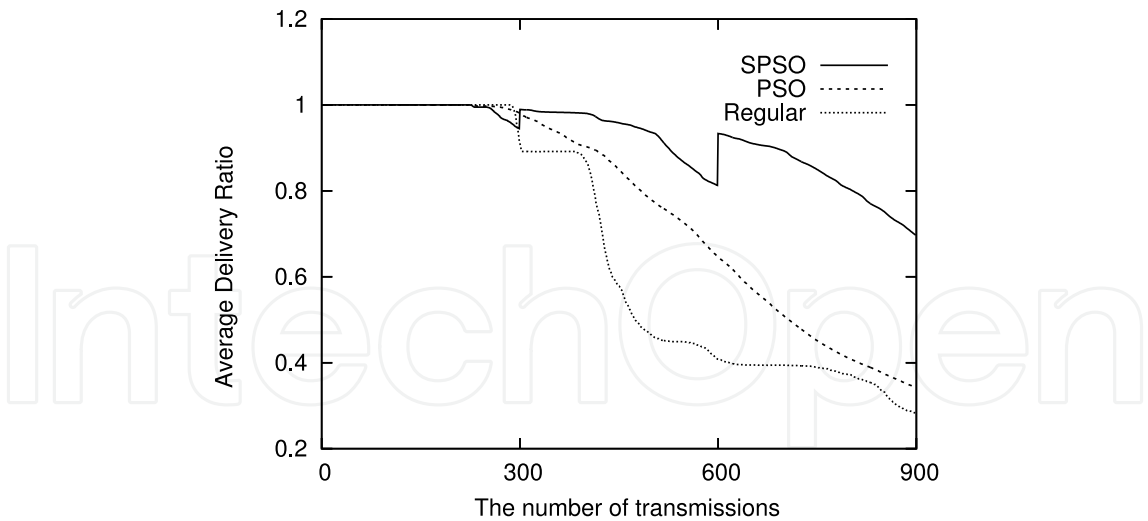


Fig. 9. Average delivery ratio for a uniform node-density wireless sensor network. SPSO: the suppression particle swarm optimization method. PSO: the particle swarm optimization method. Regular: the regular allocation method.

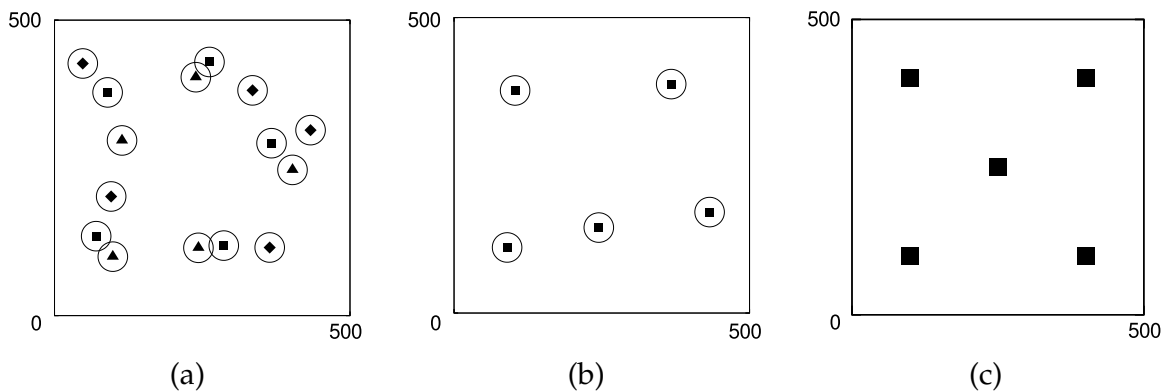


Fig. 10. Sink node allocation sets obtained by each method. (a) SPSO: the suppression particle swarm optimization method. (b) PSO: the particle swarm optimization method. (c) Regular: the regular allocation method.

But, fitness of the suppression particle swarm optimization algorithm is worse than that of the particle swarm optimization algorithm. This means that in order to prolong wireless sensor network lifetime, it is necessary to search for plural distant solutions rather than to search for a single high accuracy solution. Therefore, it is shown that the suppression particle swarm optimization method is effective for the long-term operation of wireless sensor networks.

4.4 Results for a wireless sensor network with nonuniform node-density

Next, simulation results for the wireless sensor network with nonuniform node-density shown in Fig. 4(b) are presented. Fig. 11 shows transitions of the best fitness (total hop count) in each method. In the figure, each value corresponds to the best fitness in all particles in each iteration. Table 5 shows the best fitness, the average fitness, and the average number of the solutions preserved in the memory scheme. These are the average values for 100 trials. As same as the previous experiment, in the suppression particle swarm optimization algorithm and the artificial immune system, it is possible to search widely in the solution space by the

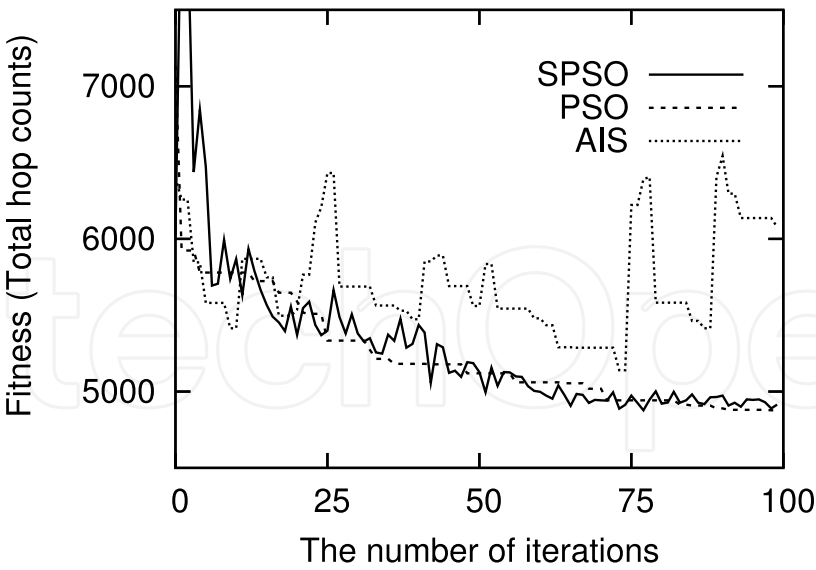


Fig. 11. Fitness in each method for a nonuniform node-density wireless sensor network. SPSO: the suppression particle swarm optimization. AIS: the artificial immune system. PSO: the particle swarm optimization.

| Algorithm | SPSO | AIS | PSO |
|---------------------|------|------|------|
| Best fitness | 4800 | 5115 | 4800 |
| Average fitness | 4979 | 5429 | 4971 |
| Number of solutions | 3.51 | 6.17 | 1 |

Table 5. Fitness and the number of solutions for a nonuniform node-density wireless sensor network. SPSO: the suppression particle swarm optimization. AIS: the artificial immune system. PSO: the particle swarm optimization.

self-control mechanism and fitness does not converge monotonously. On the other hand, in the particle swarm optimization algorithm, fitness converges to a single solution and it is not possible to search other solutions. The number of obtained solutions in the artificial immune system is the most, but fitness is the worst. The fitness in the suppression particle swarm optimization algorithm is almost the same as that in the particle swarm optimization algorithm. Fig. 12 shows three allocation sets for five sink nodes finally obtained by the suppression particle swarm optimization algorithm. Fig. 13 shows average delivery ratio for three methods. Sink node allocation sets obtained by all the methods are shown in Fig. 14.

As same as the previous experiment, the suppression particle swarm optimization algorithm can keep higher average delivery ratio than the other methods. This means that for the nonuniform node-density wireless sensor network, the suppression particle swarm optimization algorithm can also search effective sink node allocation sets. Because, it is possible to widely search on solution space. That is, the suppression particle swarm optimization method is applicable to various wireless sensor networks, and can realize long-term operation of the wireless sensor networks.

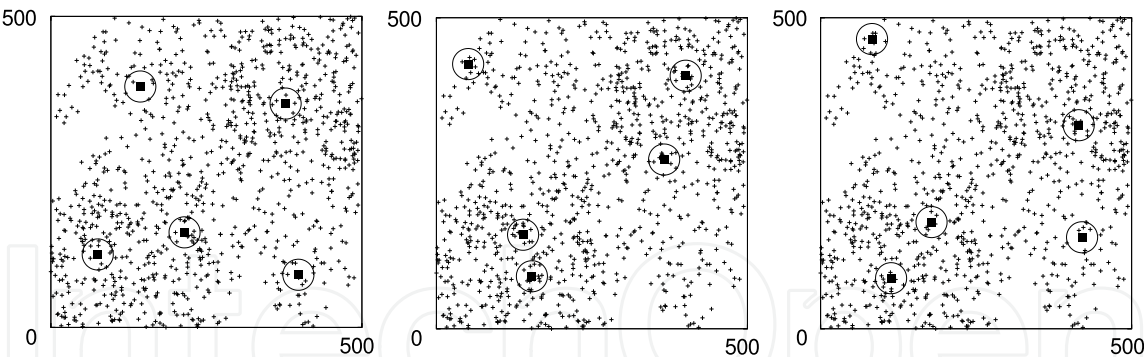


Fig. 12. Three allocation sets for five sink nodes in a nonuniform node-density wireless sensor network obtained by the suppression particle swarm optimization algorithm.

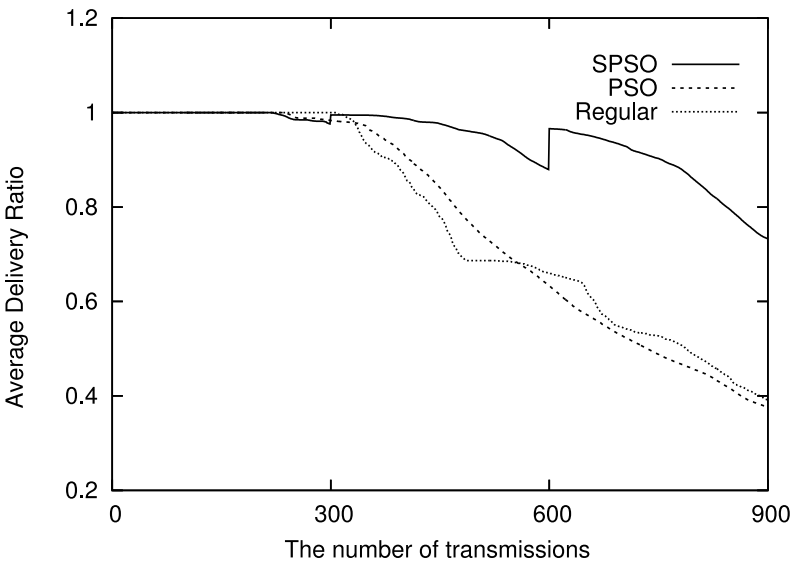


Fig. 13. Average delivery ratio for a nonuniform node-density wireless sensor network. SPSO: the suppression particle swarm optimization method. PSO: the particle swarm optimization method. Regular: the regular allocation method.

5. Conclusions

This chapter has discussed a method of placing sink nodes effectively in an observation area to use wireless sensor networks for a long time. For the effective search of sink node locations, this chapter has presented the suppression particle swarm optimization method, which is a new method based on the particle swarm optimization algorithm, to search several acceptable solutions. In the actual environment of wireless sensor networks, natural conditions or other factors may disturb the placement of a sink node at a selected location or the location effect may be lost due to the appearance of a blocking object. Therefore, it is important to provide several means (candidate locations) for sink nodes by using a method capable of searching several acceptable solutions. In the simulation experiment, the effectiveness of the method has been verified by comparison for the particle swarm optimization algorithm and the artificial immune system. Without increasing the number of search iterations, several solutions (candidate locations) of approximately the same level as that by the existing particle swarm optimization could be obtained. Future problems include evaluation for solving ability of the

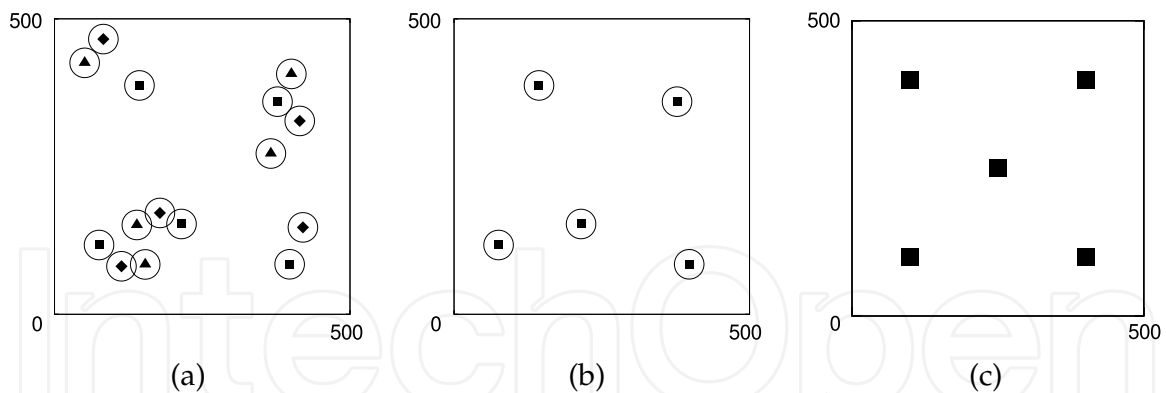
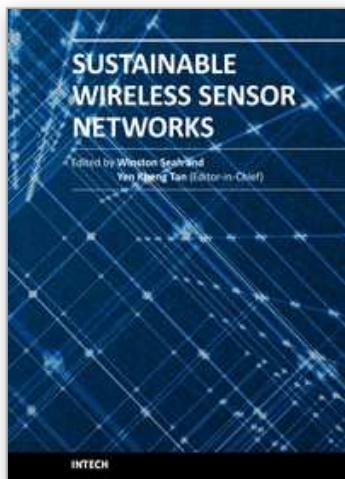


Fig. 14. Sink node allocation sets obtained by each method. (a) SPSO: the suppression particle swarm optimization method. (b) PSO: the particle swarm optimization method. (c) Regular: the regular allocation method.

method in more detail, and fusion with the existing communication algorithms dedicated to wireless sensor networks.

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Wireless Sensor Networks came into prominence around the start of this millennium motivated by the omnipresent scenario of small-sized sensors with limited power deployed in large numbers over an area to monitor different phenomenon. The sole motivation of a large portion of research efforts has been to maximize the lifetime of the network, where network lifetime is typically measured from the instant of deployment to the point when one of the nodes has expended its limited power source and becomes in-operational “ commonly referred as first node failure. Over the years, research has increasingly adopted ideas from wireless communications as well as embedded systems development in order to move this technology closer to realistic deployment scenarios. In such a rich research area as wireless sensor networks, it is difficult if not impossible to provide a comprehensive coverage of all relevant aspects. In this book, we hope to give the reader with a snapshot of some aspects of wireless sensor networks research that provides both a high level overview as well as detailed discussion on specific areas.

How to reference

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