2009 International Symposium on Nonlinear Theory and its Applications
NOLTA'09, Sapporo, Japan, October 18-21, 2009

Solving Sink Node Allocation Problems for Long-term Operation of Wireless Sensor Networks Using Suppression PSO

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Abstract—Wireless Sensor Networks (WSNs) have attracted a significant amount of interest from many researchers for a wide range of applications, such as natural environmental monitoring and environmental control in residential spaces or factories. To realize long-term operation of WSNs, we discuss in this study a method of suppressing the communication load on sensor nodes by effectively placing a limited number of sink nodes in an observation area that integrate sensing data from nodes around them. As a technique of solving effective locations for sink nodes, this paper proposes a new search method based on particle swarm optimization that is one of the swarm intelligence algorithms, named the Suppression Particle Swarm Optimization (SPSO).

1. Introduction

There is growing expectation for Wireless Sensor Networks (WSNs) as a means of realizing various applications, such as natural environmental monitoring and environmental control in residential spaces or factories. In WSNs, hundreds or thousands of micro-sensor nodes are deployed to realize environmental observation in a large-scale area and sensor information of each node is gathered to a sink node(s) by inter-node wireless communication. To realize long-term operation of WSNs, it is necessary to gather sensor information efficiently by saving node power consumption. Ant-based routing algorithms [1], and clustering-based data gathering schemes [3] are under study as communication methods to prolong the lifetime of WSNs. In past studies, we proposed an advanced ant-based routing algorithm [1] and a data gathering scheme using chaotic pulse-coupled neural network [2]. We discuss in this study a method of suppressing the communication load (transmission-reception power) 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 paper proposes a new search method based on particle swarm optimization [4]-[5] that is one of the swarm intelligence algorithms, named the Suppression Particle Swarm Optimization (SPSO) . We show that the proposed SPSO can find plural candidates for allocations of sink nodes effectively through numerical simulations.

2. Wireless Sensor Networks (WSNs)

The features of the WSNs are summarized as follows [6].

1. Sensor nodes are even to each other and realize autonomous distributed control.
2. Sensor information is exchanged directly by wireless communication.
3. Although direct communication is impossible, sensor information can be exchanged by multi-hop wireless communication.

In this paper we discuss a method of suppressing the communication load on sensor nodes by effectively placing a limited number of sink nodes in an observation area that integrate sensing data from sensor nodes around them. However, the communication load is concentrated on sensor nodes around a sink node during the operation process of WSNs and causes them to break away from the network early. Therefore, it is needed to find plural allocations of sink nodes so that total hops in all sensor nodes had are minimized, and to switch their allocations dynamically considering energy consumption of each sensor node. This problem is refereed to as a sink node allocation problem which is a kind of optimization problems.

3. Optimization Method

Generally, optimization problems in a real world require providing the effective semi-optimal solutions (acceptable solutions) in actual and reasonable computation time rather than providing a strict optimal solution in long computation time. There exist evolutionary algorithms as the method to solve such a problem. In those algorithms, an Immune Algorithm (IA) has been proposed and studied intensively [7]. 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. IA mimics such a process. IA 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. On the other hand, Particle

Swarm Optimization (PSO) is a simple and fast optimization method, and has been studied extensively [4]-[5]. In PSO each particle has a velocity vector and a position vector. The velocity vector v_{t+1} is given by the following equation.

$$v_{t+1} = wv_t + c_1 \cdot rand \cdot (pbest_t - x_t) + c_2 \cdot rand \cdot (gbest_t - x_t) \quad (1)$$

where *pbest* is a personal best solution which each particle has. *gbest* is a global best solution which all particles have. v_t is a current velocity vector. *rand* is the uniform random numbers for [0,1]. w is the inertia coefficient. c_1 and c_2 are the weight coefficients. A next position vector of the particle is given by the following equation.

$$x_{t+1} = x_t + v_{t+1} \quad (2)$$

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

4. Proposed Method

In this paper, Suppression Particle Swarm Optimization (SPSO) having a simple self control mechanism is proposed. In SPSO distance between *i*th particle and *j*th particle is calculated by Equation (3).

$$distance_{ij} = |particle_i - particle_j| \quad (3)$$

The self-control mechanism decides whether to control particles based on a density described by Equation (4).

$$Density_i = \frac{\sum_{j=1, j \neq i}^{N} \alpha(distance_{ij})}{N} \quad (4)$$

where N is a number of particles and $\alpha(x)$ is the following function.

$$\alpha(x) = \begin{cases} 1 & x \leq T_d \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where T_d is a threshold. That is, the number of particles having shorter *distance* than the threshold T_d is proportional to the density. The overall processing flow of SPSO is shown in Figure 1. As shown in the figure, a basic flow of SPSO is almost the same as that of PSO. But, “memory” and “suppression” are added to the flow of the original PSO. If a target particle has a higher evaluation value (fitness) than a threshold T_{mf}, the particle is preserved in the memory cell base on the following rules. First, the distance between all the particles preserved in “memory” and the target particle is calculated by Equation (3). When the distance is longer than a threshold T_d, the target particle is added to “memory”. On the other hand, when the distance is shorter than the threshold and the evaluation value

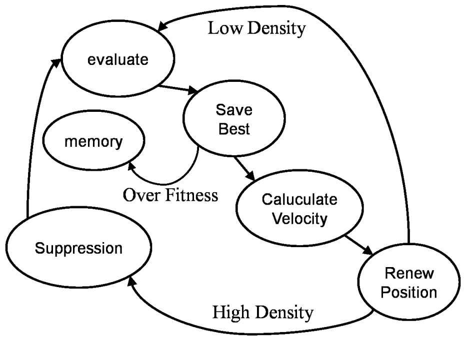

Figure 1: Processing flow of SPSO

of the target particle is higher than that of the preserved particle, the preserved particle is replaced with the target particle. “suppression” applies to the self-control if the density given by Equation (4) is higher than a threshold T_s. As the self-control is applied, the position of particles having higher densities than a threshold is rearranged randomly. Then, the value of *gbest* are held.

Applying “memory”, search of plural solutions is possible. In addition, applying “suppression” excessive conversion of particles can be controlled and search of various solutions is possible.

5. Experiment

In order to confirm effectiveness of the proposed method, three methods, IA, PSO, and SPSO, are applied to a sink node allocation problem described below, and compare the solving performances.

5.1. Sink Node Allocation Problem

The problem to allocate five sink nodes in an observation area is considered. Sink nodes can be allocated at the arbitrary positions in the area. This is a problem to search effective allocations of sink nodes in order to suppress the communication load of sensor nodes.

The evaluation value (fitness) of particles are described by the following equation.

$$fitness = \frac{1}{total\_hop\_count} \quad (6)$$

$$total\_hop\_count = \sum_{i=1}^{S} hop\_count_i \quad (7)$$

where S is the number of sensor nodes. hop_count_i is the number of hops from the *i*-th sensor node to the nearest sink node. This fitness is used for all methods : IA, PSO, and SPSO.

Parameter	Value
Area Size	500×500
Number of sensor nodes	1000
Number of sink nodes	5
Radio range	25
Number of particles	30
Total number of iterations	100

Table 1: Conditions in WSN

Parameter	Value
Interia coefficient w	0.9
Weight c_1	0.1
Weight c_2	0.1
Threshold of density T_d	30
Threshold of suppression T_S	0.7
Threshold of suppression T_{mf}	0.00016

Table 2: Parameters of optimized method

5.2. Simulation settings

The conditions in WSN are shown in Table 1. and the parameters of optimized method are shown in Table 2. The parameters in Table 2 are decided by preliminary experiments.

In order to express the position of five sink nodes in the two dimensional space, the expressions of each particle or antibody are 10 coordinate values as shown in Figure 2. Purpose of this problem is to obtain plural allocations of sink nodes to suppress communication load of sensor nodes. In order to apply each method to this problem, *distance* between each particle was defined as the minimum value of distance between sink nodes which each particle has (see Figure 3). Then, the density increases when at least two sink nodes in each particle are contiguous.

5.3. Average Delivery Ratio (ADR)

At the location provided with SPSO, lifetime of sensor nodes is calculated. Each sensor node periodically transmits sensor information to the nearest sink node. Then, the sensor node and relative relay nodes consume energy [3]. If buttery shutoff occurs in a relay node, the node can not relay sensor information. In such a situation, we evaluate average delivery ratio (ADR) for the WSN.

sink nodes	(a)		(b)		(c)		(d)		(e)	
particle	X	Y	X	Y	X	Y	X	Y	X	Y

Figure 2: Coding method to each particle

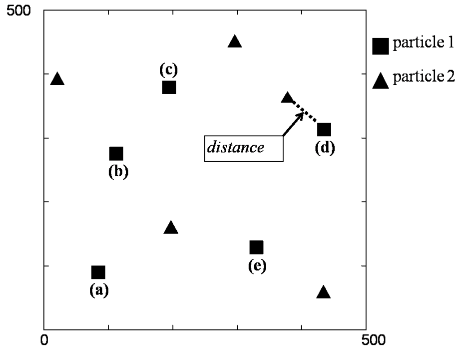

Figure 3: Definition of distance between each particle

Algorithm	SPSO	IA	PSO
Number of solution	3.73	3.44	1
Best *total_hop_count*	5274.26	5428.88	5149.33
Average *total_hop_count*	5500.55	5701.25	5382.13

Table 3: Comparison with SPSO, IA, and PSO

5.4. Result

First, transitions of the best *totalnumberofhops* in each iteration for IA, PSO, and SPSO are shown in Figure 4. In the figure, each value corresponds to the best *total_hop_count* of particles or antibodies in each iteration. Table 3 shows the average number of the solutions preserved in the memory cell, the best *total_hop_count*, and the average *total_hop_count*. These are the average values for 100 trials. In SPSO and IA it is possible to search widely in the solution space by the self-control mechanism and the number of hops does not converge monotonously. On the other hand, in PSO the number of hops converges to a single solution and it is not possible to search other solutions. As comparing quality of solutions, SPSO and IA are worse than PSO. However, it should be noted that SPSO and IA can search plural acceptable solutions while PSO can not. Next, the allocations of the sink nodes finally obtained by SPSO are shown in Figure 5. In the figure, three allocations which are preserved in the memory cell are shown, and Figure 5(a) - (c) corresponds to (a) - (c) in Figure 4. It should be noted that allocations of all the sink nodes do not overlap. This is very important in the viewpoints of suppressing communication load in each sensor node. Figure 6 shows ADR for three methods: “SPSO (change)” is the method that three allocations of sink nodes are switched in every 300 iterations. “SPSO (no change)” is the method that the best allocation of sink nodes is always selected. “Regular” is the method that sink nodes are allocated regularly in the area. It is found that ADR in SPSO is higher than that in Regular. In addition “SPSO (change)” can keep higher ADR than “SPSO (no change)”. Because, communication load in each sensors node is distributed by

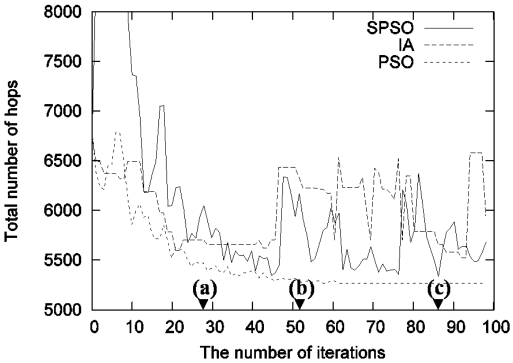

Figure 4: Total number in hops of IA, PSO, and SPSO

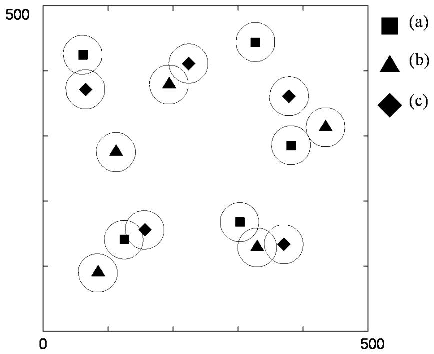

Figure 5: Three allocations of sink nodes obtained by SPSO

switching allocations. And the power consumption of all the sensor nodes is reduced. Therefore, it is shown that our method is effective for the long-term operation of WSN.

6. Conclusions

In this study, we have discussed a method of placing sink nodes effectively in an observation area to operate Wireless Sensor Networks (WSNs) for a long time. For the effective search of sink node locations, this paper has proposed Suppression Particle Swarm Optimization (SPSO). For prolonging lifetime of WSNs, it is important to provide several candidate locations for sink nodes by using a method capable of searching several acceptable solutions. In the simulation experiment, the effectiveness of the proposed method has been verified by comparison with Particle Swarm Optimization and Immune Algorithm. 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 proposed method in more detail, and fusion with the existing communication algorithms dedicated to WSNs.

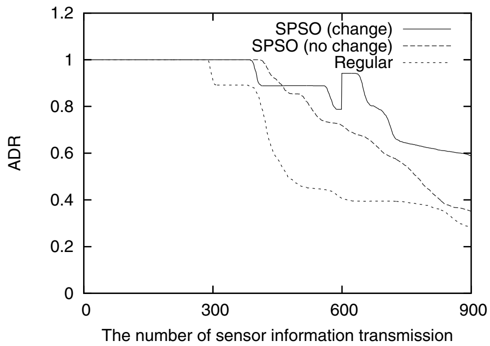

Figure 6: ADR

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