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Solving a sink node allocation problem in wireless sensor networks using a competitive particle swarm optimization

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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 method using a simple competitive PSO for finding plural acceptable solutions. The simulation results show that obtained solutions can contribute to prolonging lifetime of WSNs.

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[1]-[6]. In WSNs, hundreds or thousands of micro-sensor nodes are deployed in an observation area and sensor information of each node is gathered to sink nodes 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[2]-[3], synchronization-based data gathering schemes[4]-[5] and clustering-based data gathering schemes[6], are under study as communication methods to prolong the lifetime of WSNs. 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, we have proposed Suppression PSO (SPSO)[7] that is a fusion algorithm of Particle Swam Optimization (PSO)[8] and Immune Algorithm[9]. SPSO can find plural allocation patterns of sink nodes. As the patterns are switched dynamically, long-term operation of WSNs can be realized. However, each solution performance of SPSO is often lower than that of original PSO, and SPSO provides different number of solutions for every trial depending on initial states. In addition, SPSO has many parameters, and the control of them is difficult. This paper proposes a method using a more effective method using a simple Competitive PSO (CPSO)[10]. In CPSO plural acceptable solutions can be found by parallel processing and the control is easy by adjusting a single parameter. Through numerical simulations, we show that the proposed method can find plural candidates for effective allocations of sink nodes.

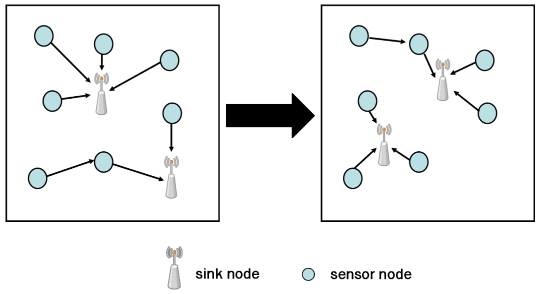

Figure 1: Sink node allocation problem

2. Wireless Sensor Networks (WSNs)

In WSNs, sensor nodes monitor status information around them in an observation area, and transmit sensing data to sink nodes by multi-hop wireless communication[1]. 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, 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, as shown in Fig.1, it is needed to find plural allocations of sink nodes so that total hops in all sensor nodes 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. For solving this problem Suppression Particle

Swarm Optimization (SPSO) has been proposed[7]. In this paper we propose a new method for long-term operation of WSNs using a simple Competitive PSO (CPSO)[10].

3. Particle Swarm Optimization (PSO)

3.1. Original PSO

Generally, optimization problems in a real world require providing effective semi-optimal solutions in actual and reasonable computation time rather than providing a strict optimal solution in long computation time. One of them, there exists Particle Swarm Optimization (PSO) as the method to solve such problems[8]. PSO is a kind of metaheuristic algorithms emulating actions in swarms such as birds and fishes. These swarms decide actions to consider status information not only as each individual but also as whole of their swarms. In PSO each particle has a velocity vector and a position vector. The velocity vector of a particle v_{t+1} is given by the following equation.

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

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. The position vector x_{t+1} of a particle is given by the following equation.

$$x_{t+1} = x_t + v_{t+1} \tag{2}$$

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.

3.2. Conventional Method: Suppression PSO

There has been a method of solving sink node allocation problems using Suppression PSO (SPSO) and the effectiveness has been presented[7]. SPSO has a simple self control mechanism and a memory mechanism like Immune Algorithm (IA)[9]. A simple self control mechanism suppresses searching plural similar solutions, and a memory mechanism saves plural different acceptable solutions. In Ref.[7], SPSO was compared with simple IA and PSO, and it was shown that SPSO was the most effective method for the sink node allocation problem. However, each solution performance of SPSO is often lower than that of original PSO, and SPSO provides different number of solutions for every trial depending on initial states. In addition, SPSO has many parameters, and the control of them is difficult.

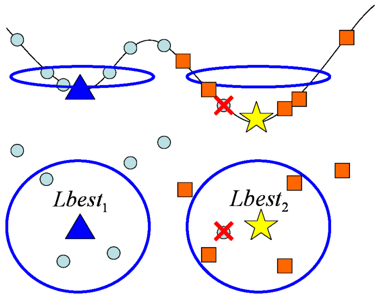

Figure 2: The priority search range

3.3. Proposed Method: Competitive PSO

In this paper, we propose a method for solving sink node allocation problem using a simple Competitive PSO (CPSO) that can efficiently find plural different acceptable solutions by dividing particles into plural groups[10]. In the original PSO, it is difficult to find plural solutions because all the particles search a single solution by moving toward global best solution. So, in the CPSO, it is considered that particles are divided into arbitrary n groups. In addition, these groups have own local best solution ($lbest$) instead of global best solution as shown in Fig.2. As a result, plural solutions can be found because particles move toward each own $lbest$. Each group has a range in which the group search a solution preferentially. If a particle belonging to the ith group goes into the range of the other group, the particle is excepted from a candidate in updating the ith $lbest$. Therefore, it is possible to search plural different solutions efficiently because each group does not go into the ranges of the other groups to each other. This range is referred to as priority search range. When a group can not search any solutions by always overlapping the ranges of the other groups, the group can obtain no solution because its $lbest$ is reset at random every time.

CPSO can effectively find desired plural acceptable solutions and can easily control them by adjusting a single parameter for the range. Also, a group with the best priority can have almost the same solution performance to the original PSO. As relative works to our method. There has been PSO with Tabu Search[11]. This method can find effective solutions using the history of personal best solutions. However, this approach is different from searching plural acceptable solutions. The proposed PSO is not sequential search method like general tabu search but a parallel search method moving priority search regions dynamically. Therefore, the proposed PSO can fast find plural solutions without repeating many trials.

4. Experiment

In order to confirm effectiveness of the proposed method, three methods, PSO, SPSO, and CPSO, are applied to a

Table 1: Conditions in WSNs

Parameter	value
Area Size	500×500
Number of sensor node	1000
Number of sink nodes	5
Radio range	25
Total number of iterations	200

Table 2: Parameters in each method

Parameter	value
Inertia coefficient w	0.9
Weight coefficient c_1	1.0
Weight coefficient c_2	1.0
No. of group	2~7
Number of particles	n ×100
Priority search range	50

sink node allocation problem described below, and compare the solving performances.

The problem to allocate five sink nodes in an observation area and to obtain plural allocation patterns is considered. Sink nodes can be allocated at the arbitrary positions in an observation area. Each particle has 10 dimensional position (and velocity) vector consisting of 2 dimensional locations of 5 sink nodes. This is a problem to search effective plural allocation patterns of sink nodes in order to suppress the communication load of sensor nodes.

The evaluation value (fitness) of each particle is defined by the following average hop counts.

$$fitness = \frac{\sum_{i=1}^{S} hop\_count_i}{S} \tag{3}$$

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: PSO, SPSO, and CPSO.

The conditions in WSNs are shown in Table 1 and the parameters of each method are shown in Table 2. They were decided in preliminary experiments. In CPSO, the number of groups, n, is changed from 2 to 7.

For the sink node locations provided with each method, 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[6]. If buttery shutoff in a relay node, the node can not relay sensor information. Each transmitting sensor node is assumed to recognize residual energy of its neighbor sensor nodes, and to select a receiving sensor node having higher residual energy. In such a situation, we evaluate Average Delivery Ratio (ADR) for the WSN.

Table 3: Fitness values in each method

	fitness						
Method	1st	2nd	3rd	4th	5th	th6	7th
PSO	5.20						
CPSO(n=2)	5.17	5.26					
CPSO(n=3)	5.16	5.22	5.43				
CPSO(n=4)	5.16	5.22	5.42	5.59			
CPSO(n=5)	5.16	5.22	5.40	5.57	5.79		
CPSO(n=6)	5.16	5.21	5.39	5.55	5.76	6.18	
CPSO(n=7)	5.16	5.22	5.39	5.57	5.80	6.36	7.27
SPSO	5.54	5.80	5.92				

Table 3 shows the average fitness in each method. These are the average values for 100 trials. In the table, sorted fitness values are shown. Comparing the original PSO and CPSO, values of the best fitness (1st) are almost the same. In CPSO parallel search is possible in the solution space by groups of particles. Therefore, two or more solutions can be obtained. Meanwhile, in PSO the fitness converges to a single solution and it is not possible to search other solutions. In CPSO in $n = 7$, the 7th fitness is much worse than the other fitness. If a group has lower evaluation value than the other groups, the priority of the group for searching solution becomes lower. Depending on the solution space, groups having lower priority might not able to find any acceptable solutions. We have confirmed that the 7th fitness does not converge.

In SPSO it is possible to search widely in the solution space by the self control mechanism and fitness does not converge monotonously. However, as comparing qualities of solutions, SPSO is worse than PSO and CPSO. In SPSO, self-control is applied if particles converge to the same position. Then, plural solutions can be obtained. This scheme causes insufficient search to each solution. SPSO has many parameters, and the control of them is difficult. On the other hand, qualities of solutions in CPSO can be controlled easily by adjusting the parameter of the priority search region, and can be better than those in SPSO. In SPSO the number of solutions saved on memory can be different for every trial. However, in CPSO the desired number of solutions can be easily obtained by changing the number of groups. Therefore, CPSO can effectively find desired plural acceptable solutions and can easily control them. They are advantages of CPSO.

Next, allocations of sink nodes finally obtained by CPSO in $n = 3$ are shown in Fig.3. In the figure, the circles represent the radio range. It should be noted that in allocations of all the sink nodes do not overlap to each other. This is very important in the viewpoints of suppressing communication load in each sensor node.

Finally, Fig.4 shows ADR for four methods: "Regular" is the method that sink nodes are allocated regularly in the area. "PSO" is the method that single allocation of sink nodes obtained by PSO is always selected. "CPSO"

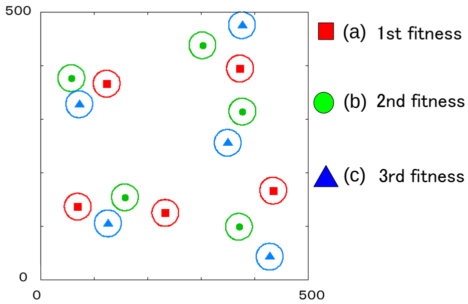

Figure 3: Three allocations of sink nodes obtained by CPSO (n = 3)

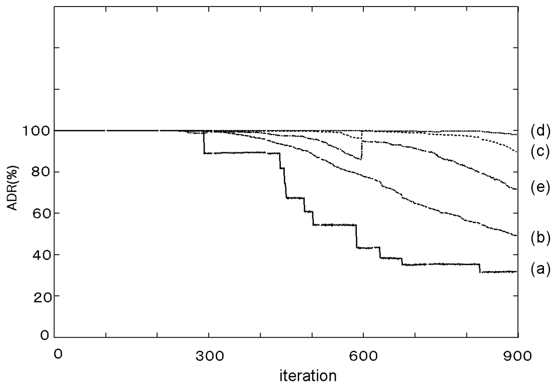

Figure 4: Average Delivery Ratio (ADR). (a) Regular. (b) PSO. (c) CPSO (n = 3). (d) CPSO (n = 6). (e) SPSO.

is the method that allocations of sink nodes obtained by CPSO are switched in every $900/n$ iteration. "SPSO" is the method that three allocations of sink nodes obtained by SPSO are switched in every 300 iteration. It is found that CPSO (n = 6) shows the best performance in all the methods. "CPSO" and "SPSO" can keep higher ADR than "PSO" and "Regular". Because, communication load in each sensor node is distributed by switching allocations of sink nodes. "CPSO" can keep higher ADR than "SPSO". Because, the energy consumption of all the sensor nodes can be balanced by switching allocations and suppressing total hops of all the sensor nodes. Therefore, it is shown that CPSO is more effective for the long-term operation of WSN.

5. 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 a method using a simple competitive PSO for finding plural acceptable solutions. 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 Suppression Particle Swarm Optimization.

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