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A Design Method for Effective Cluster-Tree ZigBee Wireless Sensor Networks Using PSO

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Abstract—ZigBee networks are expected to use various applications such as environmental observation. Nodes that form the ZigBee networks are classified into coordinators, routers, and end devices. The coordinators control the entire networks. The routers forward information measured by the end devices. It is necessary to determine appropriate allocations of the routers to build efficient networks. This paper proposes a method to solve the problem by discrete particle swarm optimization algorithms, and shows the effectiveness of the methods through the numerical experiments.

1. Introduction

The ZigBee sensor network is one of the world standards on short-distance wireless sensor networks, and can construct low-cost and low-power networks [1], [2]. This network has many applications such as voice services [3] and vehicular communications [4]. ZigBee sensor nodes are classified into Full-function Devices (FFDs) and Reduced-function Devices (RFDs). The RFD is a low-cost device and operates as a ZigBee end device which monitors status information around it, such as temperature, light intensity, and moving objects. The FFD can operate as not only a ZigBee end device but also a ZigBee coordinator or a ZigBee router which gathers sensing information transmitted from ZigBee end devices via multi-hop wireless communications. The basic networks topologies of the ZigBee sensor networks are star networks, cluster tree networks, mesh networks, and so on.

In the conventional research, an allocation method of the ZigBee coordinators in the star networks by using a Discrete Particle Swarm Optimization (DPSO, [5]) algorithm has been proposed, and the effectiveness of the method has been presented [6]. In the star networks, ZigBee routers do not exist, and there are one ZigBee coordinator and some ZigBee end devices which can directly communicate to the ZigBee coordinator by 1-hop. Each ZigBee end device does not have a routing function and only directly transmits its sensing information to the ZigBee coordinator by 1-hop. Therefore, in the case of the network topology, only small-scale sub-networks can be constructed around the ZigBee coordinator.

This paper focuses on the cluster-tree networks in which

one ZigBee coordinator and many ZigBee end devices can remotely communicate to each other by multi-hop wireless communications via ZigBee routers. Then, allocation methods of the ZigBee routers by using DPSO algorithms are discussed.

DPSO is a kind of swarm intelligence algorithms and can fast solve various optimization problems [5]. In DPSO, the particles which have discrete state variables represent solutions for objective functions, and move around multi-dimensional search space by referring to search histories of them. However, in the basic DPSO, the particles can easily trap into local optima and can not efficiently obtain plural acceptable solutions. In real problems, it is desired that specialists and engineers can select one of executable solutions from multiple solution candidates. Discrete Particle Swarm Optimization with Refractoriness (DPSO-R) is an algorithms in order to escape from local optima and obtain plural acceptable solutions [6].

In this paper, for the ZigBee router allocation problem, two methods using DPSO or DPSO-R are presented and are compared in the numerical experiments. For various ZigBee end device allocations, the performances of these methods are verified.

2. ZigBee sensor networks

The ZigBee sensor network is one of the world standards on short-distance wireless sensor networks, and can construct low-cost and low-power networks. ZigBee sensor nodes are classified into Full-function Devices (FFDs) and Reduced-function Devices (RFDs). The RFD is a low-cost device and operates as a ZigBee end device which monitors status information around it, such as temperature, light intensity, and moving objects. The FFD can operate as not only a ZigBee end device but also a ZigBee coordinator or a ZigBee router which gathers sensing information transmitted from ZigBee end devices via wireless communication. The basic networks topologies of the ZigBee sensor networks are star networks, cluster tree networks, mesh networks, and so on (see Fig.1).

The conventional research focused on the star networks. In the star networks, plural groups of one ZigBee coordinator and some ZigBee end devices exist on the whole network; ZigBee routers do not exist. Each end device

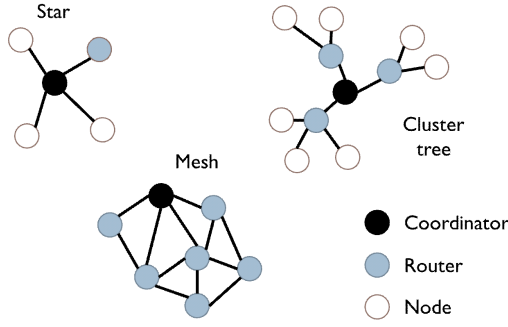


Figure 1: Basic topologies of ZigBee sensor networks.

does not have routing functions; it only transmits its own sensing information directly to a ZigBee coordinator by 1-hop, and does not relay sensing information from the other devices. Therefore, it is needed that all end devices can communicate directly to one of ZigBee coordinators via wireless communication by 1-hop, and they can construct only small-scale sub-networks in the communication range of each ZigBee coordinator. Therefore, this paper focuses on the cluster-tree networks. In the cluster-tree networks, ZigBee end devices can communicate remotely to a ZigBee coordinator via ZigBee routers by multi-hop wireless communications. Thus, large-scale networks can be constructed. In the cluster-tree networks, all ZigBee end devices and ZigBee routers have to communicate directly or remotely to a ZigBee coordinator. Therefore, the effective allocations of ZigBee routers in observation area should be considered. That is, the number of ZigBee routers and their locations should be optimized.

3. Discrete Particle Swarm Optimization

The Particle Swarm Optimization (PSO) is a kind of meta-heuristic algorithms, and can fast solve solutions in various optimization problems, compared with the other optimization methods [7]. The PSO is modeled by particles with positions and velocities in multi-dimensional search space. Each particle has a personal best solution (*pbest*) as a search history of itself and shares a global best solution (*gbest*) as a search history of all particles. The Discrete Particle Swarm Optimization (DPSO) is a discrete binary version of the PSO [5]. Basic algorithm of the DPSO is described as follows.

(step1) Set positions and velocities of each particle at random.

(step2) Update the positions of each particle by the following equation.

$$x_i^{k+1} = \begin{cases} 1, & \text{if } \rho < \sigma(v_i^{k+1}) \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$

where x_i^k and v_i^k are the position and velocity of the i -th particle at the k -th iteration, respectively. ρ is a uniform random number in the range of $[0,1]$.

(step3) Calculate evaluation values of each particle.

(step4) Update each personal best solution *pbest_i*.

(step5) Update global best solution *gbest*.

(step6) Update the velocities of each particle by the following equation.

$$v_i^{k+1} = w \cdot v_i^k + c_1 \cdot r_1 \cdot (pbest_i - x_i^k) + c_2 \cdot r_2 \cdot (gbest - x_i^k) \quad (2)$$

where w is an inertia coefficient for the current velocity vector. c_1 and c_2 are weight coefficients for personal best position vector and global best position vector, respectively. r_1 and r_2 are uniform random numbers in the range of $[0,1]$.

(step7) Set $k = k + 1$ and return to **(step2)** until the number of search iterations or the evaluation value of a solution reaches a predetermined value.

In the DPSO, there are problems that it is difficult to escape from local optima and the search for multiple solutions is not efficient. In real problems, it is desired that specialists and engineers can select one of executable solutions from multiple solution candidates. For the above requirements, the Discrete Particle Swarm Optimization with Refractoriness (DPSO-R) has been proposed [6]. In the DPSO-R, the velocities of each particle are updated by

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

where u_i^k is a refractoriness term of the i -th particle at the k -th iteration, which is given by

$$u_i^{k+1} = \delta \cdot u_i^k - \gamma \cdot \sigma(v_i^k) + \alpha \quad (4)$$

where δ is a dumping parameter, γ is a gain parameter, and α is an offset parameter. In the basic DPSO, each particle's position x is decided randomly by a uniform random number ρ . On the other hand, in the DPSO-R, ρ is set to the fixed value 0.5. If v_i^k is positive, u_i^k decreases and v_i^k decreases. If v_i^k is negative, u_i^k increases and v_i^k increases. That is, the refractoriness term can suppress the convergence of the particles.

4. Allocation Methods for ZigBee Routers

This paper proposes two allocation methods for ZigBee routers by using DPSO or DPSO-R. The observation area is delimited as grid space. Each intersection of the grid represents the candidate locations of ZigBee routers, and the combination whether ZigBee routers are allocated is optimized. The number of ZigBee routers is minimized in the constraint condition such that all ZigBee end devices and

Table 1: Environments and parameters.

Case	1	2	3
No. of end devices	20		100
Area size	20×20		50×50
Grid size	9×9	13×13	
No. of dimensions	81	169	
Radio range	5		
Coordinator location	(0,0)		
Search iterations	2,000	10,000	100,000
Number of particles	100		
S_1	100		
S_2	10		
w	1.0		
c_1	1.0		
c_2	1.0		
δ (for DPSO-R)	0.6	0.1	
γ (for DPSO-R)	1.2		
α (for DPSO-R)	0.5		

ZigBee routers can communicate directly or remotely to a ZigBee coordinator. The evaluation function is given by

$$F = \frac{S_1^{-(e_{all}-e)} \cdot S_2^{-(r_{all}-r)}}{r_{all}} \quad (5)$$

where r_{all} is the total number of ZigBee routers, r is the number of ZigBee routers which can communicate directly or remotely to a ZigBee coordinator. e_{all} is the total number of ZigBee end devices, e is the number of ZigBee end devices which can communicate to a ZigBee router or a ZigBee coordinator by 1-hop, where the ZigBee router can communicate directly or remotely to the ZigBee coordinator.

5. Experiments

The performances of the DPSO method and the DPSO-R method are compared. ZigBee end devices are allocated in the observation area at random, and a ZigBee coordinator is located at a fixed position (0,0). Table 1 shows the experimental environments for the following three cases:

Case 1: the small-scale network and the low-dimensional search space.

Case 2: the small-scale network and the high-dimensional search space.

Case 3: the large-scale network and the high-dimensional search space.

Also, Table 1 shows the parameters of each method, which are decided by the preliminary experiments. 10 trials are performed for each case by each method. Then, the finally obtained $gbest$ and $pbest_i$ solutions are evaluated, where $pbest_i$ solutions are selected so that their evaluation values

Table 2: Comparison for each method (Case 1).

Method	ANR	BNR	ANP	BNP
DPSO	10.3	9	4.2	4
DPSO-R	10.2	9	3.4	5

Table 3: Comparison for each method (Case 2).

Method	ANR	BNR	ANP	BNP
DPSO	8.3	8	6.9	10
DPSO-R	8.3	7	9.6	3

are the same as those of each $gbest$ solution. Figs.2-4 show the example allocations of ZigBee routers obtained by the DPSO-R method. Tables 2-4 show the following four metrics for each method:

- Average Number of Routers (ANR)
The average number of allocated ZigBee routers in 10 trials.
- Best Number of Routers (BNR)
The smallest number of allocated ZigBee routers in 10 trials.
- Average Number of Patterns (ANP)
The average number of allocation patterns obtained in 10 trials.
- Best Number of Patterns (BNP)
The largest number of allocation patterns obtained in trials such that the number of allocated ZigBee routers is equal to BNR.

In the small-scale networks (Cases 1 and 2), almost the same results can be obtained by both DPSO and DPSO-R methods. In addition, in Case 2, DPSO-R can find more effective allocation patterns than DPSO. These results show that DPSO-R can search widely than DPSO for the high-dimensional search space by escaping from local optima.

In the large-scale network (Case 3), the solution accuracies of DPSO-R are worse than those of DPSO. In the experiments for the DPSO-R method, the damping parameter δ is set to 0.1, that is a different value to the other cases. The higher damping parameter δ causes the stronger suppression for the convergence of the particles, but causes the slower convergence. In the preliminary experiments, the damping parameter δ is set to 0.6 and it is confirmed that $ANR = 99.4$ and $BNR = 95$. Conversely, the lower damping parameter δ causes the faster convergence of the

Table 4: Comparison for each method (Case 3).

Method	ANR	BNR	ANP	BNP
DPSO	63.4	58	3.6	5
DPSO-R	66.6	63	3.0	4

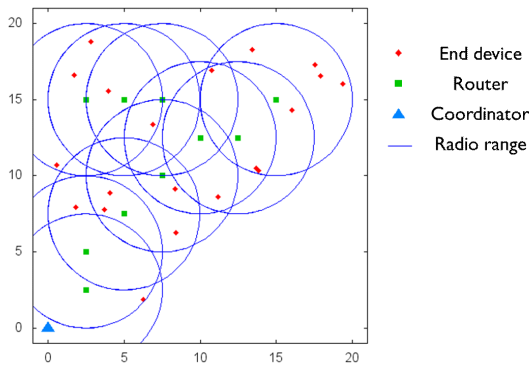


Figure 2: Allocation examples by the DPSO-R method (Case 1).

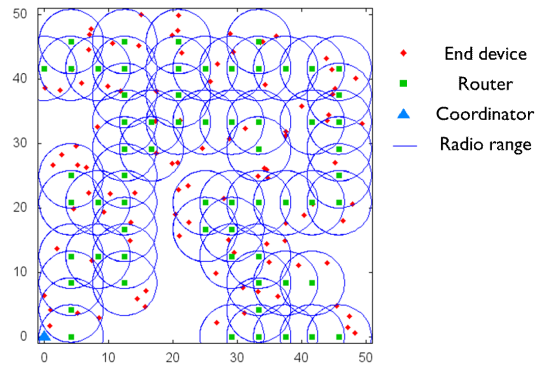


Figure 4: Allocation examples by the DPSO-R method (Case 3).

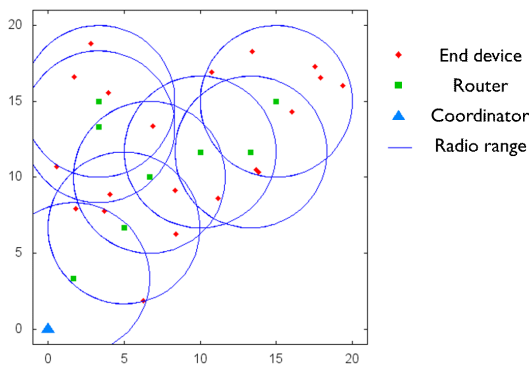


Figure 3: Allocation examples by the DPSO-R method (Case 2).

particles, but causes the weaker suppression for the convergence. For Case 3, the damping parameter δ is set to 0.1 in order to give weight to the convergence speed. Then, it is difficult to escape from local optima and the solution accuracies decrease. That is, in the refractoriness term, there exists a trade-off between extensive global search and intensive local search. For the large-scale networks, the parameter settings in the DPSO-R method should be considered in more detail.

6. Conclusions

This paper has proposed allocation methods of ZigBee routers using discrete particle swarm optimization algorithms. For the small-scale networks, the larger grid size provides better allocation patterns for ZigBee routers, and the DPSO-R method is more effective than the DPSO method. For the large-scale network, the DPSO-R method shows a little lower solution accuracies than the DPSO method. In the refractoriness term, there exists a trade-off between extensive global search and intensive local search. For the large-scale networks, the parameter settings in the DPSO-R method should be considered in more detail.

Future problems include (1) the detail analysis for the DPSO-R method, (2) the improvement of the evaluation function considering realistic conditions, and (3) the experiments in more actual sensor network environments.

References

- [1] ZigBee Alliance, <http://www.zigbee.org>, 2007.
- [2] 802.15.4-2003 IEEE Standard for Information Technology-Part 15.4, 2003.
- [3] C.Wang, K.Sohraby, R.Jana, L.Ji, and M.Deneshmand, "Voice communications over ZigBee networks," *IEEE Commun. Mag.*, vol.46, no. 1, pp.121-127, 2008.
- [4] H.M.Tsai, O.K.Tonguz, C.Saraydar, T.Talty, M.Ames, and A.Macdonald, "ZigBee-based inter-car wireless sensor networks: A case study," *IEEE Wireless Commun.*, vol.14, no.6, pp.68-77, 2007.
- [5] J.Kennedy and R.Eberhart, "A discrete binary version of the particle swarm optimization algorithm," *Proc. SMC*, pp.4104-4109, 1997.
- [6] R.Saito, et al, "Discrete PSO with refractoriness for Finding Plural Acceptable Solutions", *Proc. NOLTA*, pp.499-502, 2011.
- [7] J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization," *Proc. ICNN*, pp.1942-1948, 1995.