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CONSTRUCTION METHOD OF ZIGBEE NETWORK BY SEARCH ALGORITHMS USING ANGLE MODULATION FUNCTION

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Abstract. *Wireless sensor networks have great potential to realize state observation in large scale areas. A ZigBee network is one of the world standards for short-range wireless sensor networks. Previous studies have proposed the application of discrete binary particle swarm optimization (DPSO), which is one of the swarm intelligence algorithms, to sensor networks. However, DPSO has a problem that the performance deteriorates when the target problem becomes large scale. This paper proposes a new scheme that uses angle modulation based algorithms to detect the most effective allocation of routers in a ZigBee network. In the proposed scheme, an angle modulation function is applied to the search algorithm to generating a bit string for solving the binary problems. The performance of the proposed scheme is evaluated through simulation experiments.*
Keywords: Large scale ZigBee network, Angle modulation function, Swarm intelligence algorithms, Differential evolution

1. **Introduction.** As a key network to facilitate ubiquitous information environment, there is growing expectation for a wireless sensor network. A ZigBee network is known as a wireless sensor network technology of an open global standard [1] and has a wide range of applications, such as environmental monitoring, object tracking, inter-vehicle communication which is a network service in intelligent transport systems, and precision agriculture. Types of ZigBee devices include ZigBee coordinator, ZigBee router, and ZigBee end device [2]. ZigBee coordinators and ZigBee routers have a function for relaying data, while ZigBee end devices do not. The topology of a ZigBee network includes a star network consisting of a single ZigBee coordinator and several ZigBee end devices, and a tree network and mesh network consisting of a ZigBee coordinator, ZigBee routers, and several ZigBee end devices. This study focuses on tree networks. It is required that each ZigBee end device can directly send its own sensing data to one of the routers via wireless communication. Therefore, the effective allocation of ZigBee routers in an observation area should be achieved. This means the number of ZigBee routers and their locations should be optimized. This paper proposes a new scheme based on angle modulation (AM) based algorithms [3-5] to detect the effective allocation of routers in a ZigBee network. The AM based algorithms are promising methods for combination optimization problems. In the proposed scheme, an observation area is represented as a grid space, and a search algorithm is used to determine whether to allocate a router on each intersection of the grid. In the simulation experiments, we demonstrated that our proposed scheme provided superior results in large-scale area such as hundreds or thousands of dimensions compared with other related ones. The rest of the paper is organized as follows. Section 2 outlines discrete binary particle swarm optimization (DPSO). In Section 3, we describe the proposed scheme based on AM based algorithms and construction method of ZigBee

networks. In Section 4, the experimental results are reported in detail. Finally, this paper closes with conclusions and ideas for further study in Section 5.

2. **Discrete Binary PSO [6-8].** DPSO is a method for combination optimization problems based on particle swarm optimization (PSO) [9], which belongs to the broad class of stochastic optimization methods. In PSO, each particle constituting a swarm searches for a solution until a predetermined iteration is reached using the personal best solution ($pbest_{id}^k$) and the global best solution shared in the swarm found during the search process ($gbest^k$). Each particle produces a new velocity vector (v_{id}^{k+1}) by linearly coupling the previous velocity vector (v_{id}^k), $pbest_{id}^k$, and $gbest^k$ before moving to the next position (x_{id}^{k+1}). Assume an n-dimensional search space, and a swarm consisting of N particles. Superscript k indicates the number of iterations, subscript d ($d = 1, \ldots, n$) represents the index of the variable, and subscript i ($i = 1, \ldots, N$) represents the index of the particle. At the $k+1$ iteration, the velocity vector (v_{id}^{k+1}) and position vector (x_{id}^{k+1}) of the i-th particle are updated by the following equations

$$v_{id}^{k+1} = \omega \cdot v_{id}^k + c_1 \cdot r_1 \cdot \left(pbest_{id}^k - x_{id}^k\right) + c_2 \cdot r_2 \cdot \left(gbest^k - x_{id}^k\right) \tag{1}$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{2}$$

where r_1 and r_2 are random numbers, uniformly distributed within the interval $[0, 1]$. ω is a parameter called the *inertial weight.* c_1 and c_2 are positive constants, which are referred to as the *cognitive* and *social* parameters, respectively.

In DPSO, each element (variable) of the position vector of each particle is transformed from the variable of continuous type of the binary state variable, i.e., 0 or 1, according to the following rule

$$\begin{aligned} \text{if } \rho < sig\left(v_{id}^{k+1}\right) \quad &\text{then } x_{id}^{k+1} = 1; \\ &\text{else } x_{id}^{k+1} = 0 \end{aligned} \tag{3}$$

$$sig\left(v_{id}^{k+1}\right) = \frac{1}{1 + \exp\left(v_{id}^{k+1}\right)} \tag{4}$$

where $sig(\cdot)$ is the sigmoid function. ρ is a random number, uniformly distributed within the interval $[0, 1]$. The method of updating the velocity vector (v_{id}^{k+1}) is the same as that in the PSO. The value of position vector (x_{id}^{k+1}) is determined by comparing the results of the sigmoid function with ρ.

Problems of DPSO. DPSO used in previous studies has two problems. Firstly, DPSO is that the performance deteriorates when the target problem becomes large scale. Secondly, in PSO, on which DPSO is based, it is difficult to escape from the local solution. Therefore, the solution search stagnates. In addition, when the target problem becomes higher-dimensional, the number of local solutions also increases, which causes the solution search to stagnate even more. Hence, new algorithms for constructing large scale ZigBee network are needed.

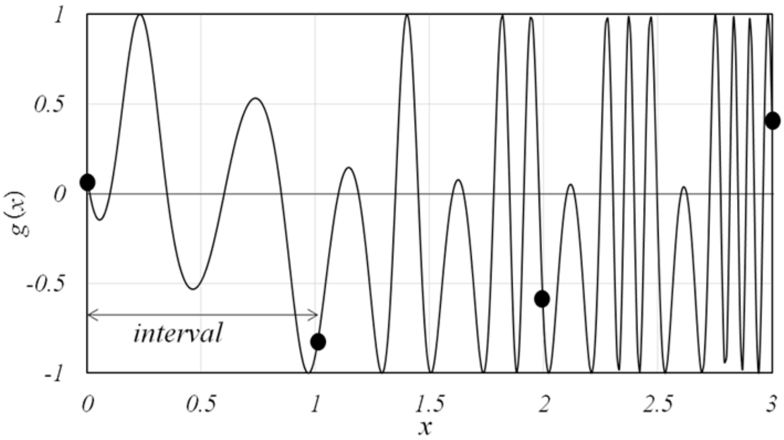
3. **Proposed Scheme.** In the proposed scheme, the optimum number of ZigBee routers and locations is found using an AM based algorithm. In this section, we detail the proposed scheme.

3.1. **AM based algorithms.** The angle modulation based algorithms are normal search algorithms that uses a trigonometric function as a bit string generator. As shown in Equation (6), the AM function consists of trigonometric functions and four variables.

$$\begin{aligned} \text{if } g(x) \geq 0 \quad &\text{then } bin = 1; \\ &\text{else } bin = 0 \end{aligned} \tag{5}$$

$$g(x) = \sin(2\pi(x - a) \cdot b \cdot \cos(2\pi(x - a) \cdot c)) + d \tag{6}$$

where $g(\cdot)$ is the AM function, the coefficient a represents the horizontal shift of the function, b is maximum frequency of the sin function, c is maximum frequency of the cos function and d represents vertical shift of the function. In the continuous-valued optimization algorithms, these four variables are used to obtain a bit string of an arbitrary length. Figure 1 shows the waveforms of the AM function at $a = 0.6$, $b = 1.0$, $c = 1.0$, $d = 0$ and bit string at $interval = 1.0$. $interval$ is the control value of the input value x ($= interval \times i$) to the AM function. If the generated output value of $g(\cdot)$ from Equation (6) is positive, a bit value is 1; otherwise a bit value is 0. A bit string of arbitrary length is generated by these processes.



input-values	0	1	2	3
bit-values	1	0	0	1

($interval = 1$)

Figure 1. Bit string generation by the angle modulation function

The advantage of AM based algorithms compared with DPSO is that the search performance is less likely to deteriorate even when the target problem becomes large-scale. For example, when the target problem consists of 100 dimensions, the DPSO must optimize the position vector by updating 100 elements, whereas the AM based algorithm only needs to optimize four variables regardless of the number of dimensions of the target problem. AM based algorithms include AMPSO [3] applying AM function to PSO, AMDE [4] applying AM function to differential evolution method [10], AMABC [5] applying AM function to artificial bee colony algorithm. There are only a few examples where AM based algorithms have been applied to real problems. In addition, although these performance evaluation experiments are carried out in [3-5], the number of dimensions of the target problems is too low. Therefore, the difference with DPSO (BinPSO in [3-5]) is not clear. In this paper, we show an application example to the ZigBee router placement problems described later, and clarify the effectiveness of the AM based algorithm by combination optimization problems consisting of several hundreds to thousands of dimensions.

3.2. **Construction method of ZigBee network.** In this paper, an observation area is represented as a grid space as shown in Figure 2. In the proposed scheme, each intersection of the grid is modeled as the candidate location of a ZigBee router. The proposed scheme decides whether a router is allocated on each intersection of the grid or not in the situation that ZigBee end devices have been randomly placed in a given observation area. In other words, on the ZigBee end devices set at random, the combination solution whether a router is allocated on each intersection of the grid or not is searched by the proposed scheme based

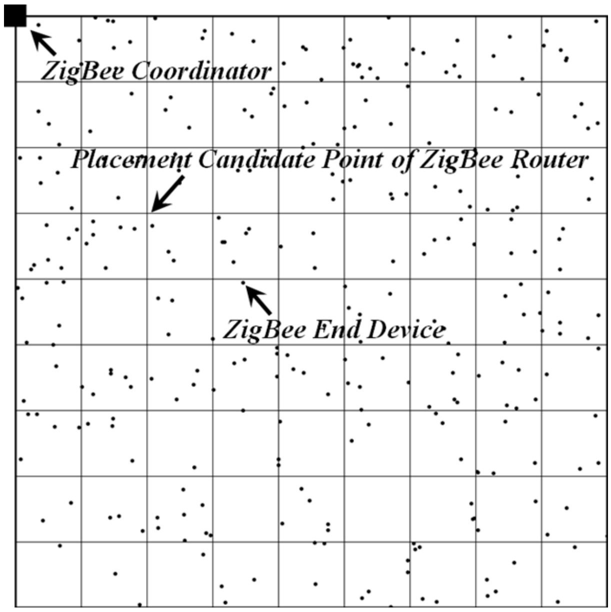


FIGURE 2. Grid division of an observation area and the position of each device

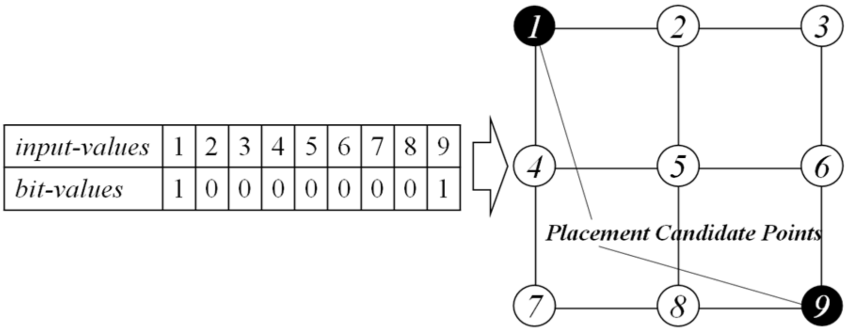


FIGURE 3. Allocation of input-values to placement candidate points

on AM based algorithms. Input-values to AM function are allocated to each placement candidate point as shown in Figure 3. In the above combination optimization problem, it is required that each ZigBee end device can directly send its own sensing data to one of the routers via wireless communication. In such a constraint condition, the combination solution aiming to minimize the number of the routers allocated is searched. A low-cost large-scale sensor network can be constructed by reducing the number of routers using the proposed scheme. The evaluation of the solution in the ZigBee router placement problems is performed in the following procedure.

Procedure for router placement detection is as follows.

Step 1: Each ZigBee end device checks whether there is ZigBee router within radio range and, if such a router exists, the ZigBee end device is defined as a communicable ZigBee end device.

Step 2: Count the number of communicable ZigBee end devices.

Step 3: Each ZigBee router initiates flooding and checks whether it can communicate with ZigBee coordinator. If it can communicate with ZigBee coordinator, the ZigBee router is defined as a communicable ZigBee router.

Step 4: Count the number of communicable ZigBee routers.

Step 5: The evaluation value is calculated by the objective function $f(x)$.

The objective function $f(x)$ is formulated aiming to satisfy two conditions as follows.

1) All ZigBee end devices communicate directly with ZigBee routers.

2) All ZigBee routers communicate indirectly with a ZigBee coordinator by multi-hop communication.

The objective function $f(x)$ for the minimization of the number of ZigBee routers is set as follows

$$f(x) = R_{all} \cdot S^{(E_{all}-E_{num})+(R_{all}-R_{num})} \tag{7}$$

$$\text{if } R_{all} = 0 \quad \text{then } f(x) = \infty \tag{8}$$

where E_{all} is the total number of ZigBee end devices, and E_{num} is the number of ZigBee end devices that can communicate directly with ZigBee routers. R_{all} is the total number of deployed ZigBee routers, and R_{num} is the number of ZigBee routers that can communicate indirectly with the ZigBee coordinator. S is the base of the exponent (constant). When all distributed ZigBee end devices and all the ZigBee routers placed by the bit string satisfy the above two conditions, the objective function $f(x)$ is equivalent to the number of placed ZigBee routers. DPSO and AM based algorithms search for solutions (bit string) that minimize the evaluation value of the objective function $f(x)$.

4. **Simulation Experiments.** A simulation experiment was conducted on a ZigBee network consisting of 300 end devices, and we evaluated the effectiveness of the proposed scheme compared with that of DPSO.

4.1. **Conditions of simulation and parameter setting.** A ZigBee network composed of static sensor nodes, i.e., ZigBee end devices placed in a 500m×500m square observation area (grid 20 × 20 to 50 × 50) was assumed. A ZigBee coordinator is placed in advance at the upper left of the observation area, and several ZigBee routers are deployed by the proposed method for constructing a tree network. Table 1 shows the conditions of simulation, Table 2 shows common parameter settings on each algorithm, and Table 3 shows parameter settings on each algorithm. In addition to referring to the values used in [3-5] in the parameter set values, values obtained by good results in preliminary experiments are adopted. The compared algorithm includes DPSO, AMPSO, AMDE, and AMABC. The selected values of the parameters (ω, c_1, c_2) are considered proper default values and they are widely used in the relevant literature on the discrete binary PSO. In addition, the constant S of the objective function $f(x)$ is set as $S = 1.2$ in the case of 2500 dimensions, and $S = 2.0$ in other cases.

4.2. **Experimental result.** Based on the simulation environment described above and parameter settings on each algorithm, the results of the best value (Best), average value (Average), and worst value (Worst) of the objective function value $f(x)$ obtained by 50 trials of the simulation experiment are shown in Table 4. In addition, as an example of the solution constructed by the proposed method, the best solution (Best) of 2500 dimensions calculated by the AMDE is shown in Figure 4.

Table 1. Conditions of simulation

Simulation size	500m × 500m
The number of ZigBee end devices	300
Radio wave range of ZigBee end device	100m
Radio wave range of ZigBee rooter	100m

Table 2. Common parameter settings on each algorithm

Trials	50
Iterations	1000
Dimensions	The number of grids
interval (AM)	1.0

Table 3. Parameter settings on each algorithm

Algorithm	Parameter	Value
DPSO	particle size	60
	c_1, c_2	2.0
	ω	1.0
	$V_{\max}$	
AMPSO	particle size	60
	c_1, c_2	2.0
	ω	1.0
	$V_{\max}$	4.0
AMDE	population size	60
	crossover ratio	0.9
	mutation factor	0.5
	mutation type	DE/rand/1
	crossover type	exponential
AMABC	colony size (N)	60
	employed bees (SN)	50% of colony size
	outlookers (N-SN)	50% of colony size
	limit	0.1 × SN × Dim.

Table 4. Experimental results (50 trials)

Grid	Dims.	Algorithm	Best	Average	Worst
20 × 20	400	DPSO	22	25.64	29
		AMPSO	22	25.18	27
		AMDE	22	23.7	25
		AMABC	25	33.14	41
30 × 30	900	DPSO	23	26.86	31
		AMPSO	23	25.36	28
		AMDE	22	23.56	26
		AMABC	23	36.74	41
40 × 40	1600	DPSO	22	26.76	35
		AMPSO	22	24.42	27
		AMDE	19	22.72	24
		AMABC	23	34.88	43
50 × 50	2500	DPSO	105	125.54	148
		AMPSO	22	24.44	27
		AMDE	20	22.52	24
		AMABC	21	31.74	42

Table 4 shows the number of the deployed ZigBee routers. Figure 4 shows that a tree network is constructed by the proposed method. It should be noted that the proposed scheme based on angle modulation based algorithms can find acceptable solutions in large scale areas such as a 50 × 50 grid space (2500 dimensions). There is not much difference between DPSO and AM based algorithms at 20 × 20 grid space (400 dimensions). However, DPSO gets worse when the target problem becomes large scale such as 50 × 50 grid space (2500 dimensions). AMDE has the best value in all of best, average and worst. AMDE has superiority compared with other algorithms in the experiments.

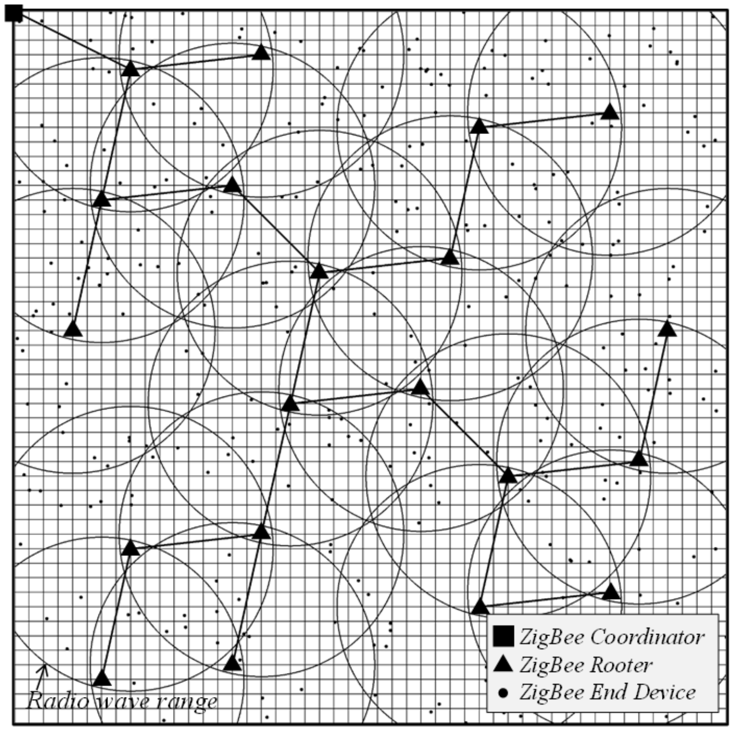


Figure 4. An example of constructed by the proposed method (2500 dimensions)

5. **Conclusions.** In this paper, we have proposed a new scheme based on angle modulation based algorithms to optimize the allocation of ZigBee routers in ZigBee network and have confirmed its effectiveness. The proposed scheme can provide the ZigBee router allocation that the number of ZigBee routers is minimized and all ZigBee end devices can be directly connected with one of ZigBee routers via wireless communication. In addition, we confirmed the superiority of AMDE by simulation experiments of hundreds or thousands of dimensions. Future work includes a detailed evaluation of the proposed scheme in large scale ZigBee networks and various ZigBee sensor applications.

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