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Optimization and Energy-saving Deployment of Nodes in Wireless Sensor Network

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Abstract. Aiming at the problem of energy conservation and optimal deployment of WSN, this paper establishes an optimal coverage model. Meanwhile, an energy saving deployment algorithm is proposed based on the particle swarm theory and quantum behaved particle swarm optimization. The quasi physical strategy, namely the quasi-gravitation and quasi-coulomb force, are introduced in the position evolution equation of quantum particle swarm optimization algorithm, which can regulate the distance between the sensor nodes reasonably. Also, the algorithm can obtain the fast optimization with low regional repetition rate. In addition, the sensing radius of WSN nodes is adjusted dynamically in order to minimize the node energy consumption. The simulation results show that the proposed algorithm has better performances in terms of network coverage rate and convergence speed, compared to the traditional particle swarm and quantum behaved particle swarm optimization schemes. At the same time, the algorithm has certain advantage in reducing the node energy consumption in WSN.

Keywords: optimal deployment, quantum particle swarm, quasi physical strategy, wireless sensor network

1 Introduction

Wireless Sensor Network (WSN) has become a newly hot and front research area. It is a subject that combines with sensor technology, embedded computing technology, distributed information processing technology and communication technology, etc. It has been a revolution of information sensing, collecting and processing. Micro-sensor technology supported by Micro-Electro-Mechanical Systems and wireless communication capabilities for sensor network give a broad application prospect for WSN.

WSN is composed of a large number of low power micro sensors, whose nodes can sense various physical phenomena in industrial, military and other environments, such as sound, light, temperature, and movement etc. The nodes can process the original sensing data and transmit data to the sink node in wireless multi hop routing [1]. The sink node sends the collected data to a wireless network or local area network. It greatly improves the accuracy and sensitivity of the data and information.

WSN have the advantages of high precision monitor, strong fault tolerance, large coverage area, and capable of remote monitoring. It has been widely used in military and national defense, national security, environmental monitoring, target tracking, medical and health, combating terrorism, intelligent building, environmental science and space exploration and other fields [2-3]. Sensor nodes have limited capabilities due to small storage, low power due to battery equipped, communication cost and limited processing capabilities [4]. Therefore, the sensor node is susceptible to node failure. This type of node failure causes coverage hole in the network and the sensed data cannot be transmitted between nodes. This paper focuses on the critical problem in WSNs, called deployment of sensor nodes.

In the paper, an optimization node deployment scheme in WSN to improve area coverage and network lifetime is discussed. The reminder of this work is organized as follows: section 2 deals with the background of coverage and connectivity in WSN, section 3 gives the coverage optimization objective

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function and coverage model, section 4 proposes an improved node coverage optimization algorithm to provide energy-saving coverage in WSN, section 5 provides the coverage comparison of different algorithms and discussion of factors affecting the coverage. Section 6 presents the conclusion of this work and directions for future research.

2 Related Works

Swarm intelligence algorithm is a kind of optimization calculation method, and its application in network coverage optimization is increasing recently. Particle swarm optimization (PSO) algorithm is a stochastic global intelligent optimization algorithm, which is put forward according to the social simulation model [5]. The idea of PSO is to use a group of particles in the optimization area for random search, to complete the optimization. With the continuous research of PSO algorithm, some improved algorithms have been widely used in the fields of biomedicine, communication network and automatic control. Also, there are many applications in the WSN network positioning, coverage and so on.

Owing to few adjustable parameters, fast convergence rate and easily to be realized [6], PSO has attracted the attention of the majority of researches. In the space search, the particle's flight speed directly affects the global convergence of the algorithm. The particle velocity is relatively large, which can guarantee the faster flight to the global optimum solution. However, there is no restriction on the particle flying, causing optimal solution might be easily missed. Moreover, PSO is easy to fall into local extremum, premature convergence and stop state, which restrict the improvement of coverage performance in WSN. It has been proved that PSO algorithm is not a global convergence algorithm [7].

The PSO improvement research is mainly implemented in two aspects: (1) adding a variety of optimization methods on the basis of the traditional PSO algorithm; (2) combining the existing intelligent optimization strategy and the PSO algorithm. In [8], a WSN coverage optimization strategy is proposed to judge the value of the PSO algorithm by dimension.

Though the solution accuracy is improved and the convergence speed of the algorithm is accelerated, the problem of premature convergence of the particle still cannot be overcome. The principle of chaotic tent mapping is applied to the PSO algorithm in [9]. The method involves the mapping and inverse mapping of chaotic variables, which enhances the convergence ability of the algorithm while increasing the complexity of the algorithm. Moreover, the quantum behaved particle swarm optimization (QPSO) algorithm is proposed [10], in which each individual is described by a particle in the quantum space. The potential energy field model for the particle is given in the literature [11], and the QPSO is proved to be a kind of global convergence algorithm. QPSO algorithm improves the behavior of the particles, so that the particle can search in the whole feasible solution space. It overcomes the problem of premature convergence and local optimum of PSO algorithm, and improves the global optimization ability.

Among recent work, Vidhi Jindal et al. [12] proposed a novel sensor node distribution strategy and sink mobility model, to increase the network lifetime and prevent fast depletion of sensor node energies. The strategy implements sleep scheduling for a subset of nodes based on the current position of the mobile sink. Amir Javadpour et al. [13] proposed an optimization particle swarm and fuzzy logic to improve energy consumption for routing in WSN. Virtual force algorithm for multi-robot deployment is introduced in [14]. Their research investigated the best setting for factors of the attractive force and repulsive force. In addition, they introduced an energy-aware virtual force approach in order to maximize network lifetime and minimize power consumption among deployed robots.

3 WSN Coverage Optimization Model

Assuming that N nodes are randomly deployed in the two-dimensional monitoring area, which is represented as $N=\{n_1, n_2, \ldots, n_N\}$and the coordinates of the node n_i expressed by (x_i, y_i). The area is discretized into $B\times C$ grid points and the coordinates of each grid point is (x, y), $x \in B$, $y \in C$. The minimum number of nodes needed in the area A_{area} is related to the sensing radius r of the nodes in [15]. The r is the maximum monitoring area that can be sensed by the node, and the value is usually determined by the hardware characteristics of the node itself. In addition, assuming that the communication radius of WSN nodes is larger than or equal to two times of the sensing radius r, in order to ensure full connection of the network. Therefore, the problem of coverage connectivity can be transformed into a separate coverage control problem.

Based on the above assumptions, the duality perceptive model of grid point (x, y), covered by the WSN node, is

$$p = \begin{cases} 1 & \text{if } d \le r \\ 0 & \text{else} \end{cases} . \quad \textbf{(1)}$$

where d is the distance from the WSN node to any grid point, which can be written as

$$d = \sqrt{(x - x_i)^2 + (y - y_i)^2} . \quad \textbf{(2)}$$

When the grid point (x, y) is covered by a number of WSN nodes, the coverage probability of the grid points is 1, regardless of the number of nodes. As a result, the total number of grid points covered by the target monitoring area is

$$Num_{\text{cov}} = \sum_{B \times C} p . \quad \textbf{(3)}$$

Thus, the coverage rate of the WSN node in the target area A_{area} can be written as

$$P_{\text{cov}.A} = \frac{Num_{\text{cov}}}{B \times C} . \quad \textbf{(4)}$$

Equation (4) is the objective function of the WSN coverage optimization algorithm.

The energy consumption of WSN is mainly embodied in three aspects: communication energy consumption, computation energy consumption and sensing energy consumption. The communication cycle of the WSN node includes sleep, idle, transmission and reception. The experiments in [16] show that the communication and calculation energy consumption of WSN nodes are much higher than the sensing energy consumption. This paper mainly studies the WSN coverage problem, focusing on the node's perception energy consumption, less considering the communication and calculation energy consumption.

Assume that the energy consumption of the node in sleep state is 0. Let E and r denote the energy consumption and sensing radius of a node, respectively. The relation of E and r can be represented by Equation (5).

$$E = kr^2 . \quad \textbf{(5)}$$

Usually, k is a constant greater than 0, typically k=1.

By adjusting the sensing radius of WSN nodes, it can effectively improve network coverage and reduce sensing energy consumption [17]. Let $r_1, r_2, \ldots, r_N$ be the sensing radius of N nodes, then the total sensing energy consumed by WSN in deployment is

$$E_{H-total} = u \times \sum_{i=1}^{N} r_i^2 . \quad \textbf{(6)}$$

where u is a constant greater than 0, usually, u=1.

Assuming that all WSN nodes in the target monitoring region A_{area} have the same initial energy, i.e. the same initial sensing radius, and each node has the ability to self-regulate the sensing radius. The sensing radius set of nodes can be expressed as $\{r_1, r_2, \ldots, r_N\}$, $r_{\min} \le r_i \le r_{\max}$. According to Equation (5), the maximum sensing consumption of each node is r_{max}^2, and the maximum sensing energy consumption of the WSN network is Nr_{max}^2. The coverage optimization model is established based on maximizing the network coverage as the optimization function, while reducing the network sensing energy consumption is taken as the constraint condition, by

$$\begin{cases} Max \quad P_{\text{cov.A}} = \dfrac{Num_{\text{cov}}}{B \times C} \\ s.t. \quad \sum_i r_i^2 < N \cdot r_{\max}^2 \end{cases} . \quad \textbf{(7)}$$

4 QPSO-Based Energy Saving Coverage Optimization

4.1 QPSO Algorithm

In quantum space, the position of the particle can be determined, but the velocity is uncertain. In this case, the wave function $\Psi(x)$ describes the state of particle. In the D dimensional target area, assuming that the $X_i(t)$, $P_i(t)$ and $P_g(t)$ represent the current position of particle i, the optimal location of particle i and the optimal position of particle swarm respectively, then the expression is [18]

$$\begin{cases} X_i(t) = (x_{i1}(t), x_{i2}(t), ..., x_{iD}(t)) \\ P_i(t) = (p_{i1}(t), p_{i2}(t), ..., p_{iD}(t)) \\ P_g(t) = (p_{g1}(t), p_{g2}(t), ..., p_{gD}(t)) \end{cases} . \quad \textbf{(8)}$$

The particle state represented by $\Psi(x)$ satisfies the following expression

$$\int_{-\infty}^{+\infty} |\psi(x)_i|^2 \, dxdy = \int_{-\infty}^{+\infty} Q dxdy = 1 . \quad \textbf{(9)}$$

where Q is the probability corresponding to the particle appearing in the position (x, y). The particle position update can be obtained according to Monte Carlo method, as

$$\begin{cases} Q(t) = X(t) \pm \frac{L}{2} In(\frac{1}{u}) \\ X(t) = \alpha P_i(t) + (1-\alpha) P_g(t) \\ P_{avg}(t) = \frac{1}{M} \sum_{i=1}^{M} P_i \\ L(t+1) = 2\beta \,|P_{avg}(t) - Q(t)| \\ Q(t+1) = X(t) \pm \beta \,|P_{avg}(t) - Q(t)| \ln(\frac{1}{u}) \\ \beta = 0.5 + \frac{(1-0.5)(t_{\max} - t)}{t_{\max}} \end{cases} . \quad \textbf{(10)}$$

where $X(t)$ is a random position between $P_i(t)$ and $P_g(t)$, i.e., the current location of particle i, u and α is random number between (0, 1), respectively; M is the population of particles; $P_{avg}(t)$ is the optimal location for all particles; $t_{\max}$ is the maximum iterations number. If $u \leq 0.5$, the sign before β is "+", on the other hand, the symbol is "-". The parameter β represents the velocity of particle convergence, which is favorable for particle convergence when β=0.8.

4.2 The Quasi Physical Strategy

Quasi physical force is a kind of heuristic intelligent optimization algorithm, which is first put forward to solve the NP problem. The quasi-gravitation and quasi-coulomb force, are introduced to solve the problem of WSN coverage optimization in the literature [19].

Quasi-gravitation model: It is assumed that N nodes with sensing radius r are randomly deployed in the two-dimensional area of A_{area}, and the sensing region of the node is regarded as N disks. Discretization of the region into K grid points, as a particle, as shown in Fig. 1. In the figure, if the particle A is not covered, it will produce a gravitational force on its neighbor disk 2 and 3. And, if the particle A has been covered, it will automatically shield disk 1, 2 and 4, i.e., no gravity for disk 1, 2 and 4. Thus, the quasi-gravitation expression of the disk i by the force of particle k, is [15]

$$f_{ik} = \begin{cases} \frac{r_i^2}{d_{ik}^2}, v_k \notin \bigcup_{n=1}^{N} S_n, \; R_{\mathrm{i}} \geq d_{ik} > r_i \\ 0, \quad \text{else} \end{cases} . \quad \textbf{(11)}$$

where d_{ik} is the distance between particle and the center of disk, r_i^2 is the weight of disk, $v_k \notin \bigcup_{n=1}^{N} S_n$ indicates that only the particles that are not covered have gravitational effects on the disk, and the inequality $r_i < d_{ik} \le R_i$ determines the scope of gravity.

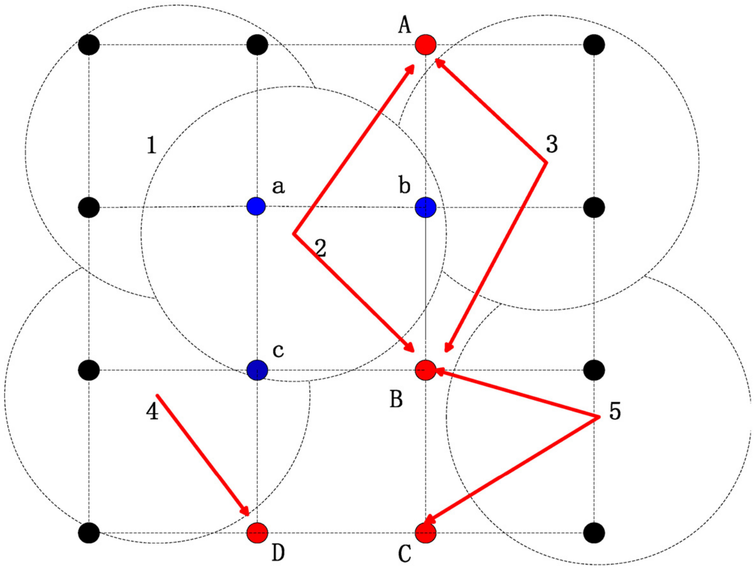


Fig. 1. The model of quasi-gravitation and quasi-coulomb force

Quasi-coulomb force model: In addition to gravitation, a disk is also subjected to repulsion from other disks, which are called quasi coulomb forces. When the disk does not cover the particle completely, the quasi coulomb force is in a failure state. When repulsion becomes the dominant force of moving disk, that is, all particles are covered. This improves coverage performance by making the disc distribution more evenly and avoiding redundant repeat coverage. The quasi coulomb force is defined as

$$f_{ij} = \begin{cases} 0, & \text{else} \\ \dfrac{r_i^2 r_j^2}{d_{ij}^2}, & \mathrm{d_{ij}}<\min\left\{R_i, R_j\right\} \end{cases} . \tag{12}$$

where d_{ij} is the distance between two nodes, the inequality $d_{ij} < \min\left\{R_i, R_j\right\}$ limits the range of repulsive forces between neighbor nodes.

4.3 Energy Saving Coverage Optimization in WSN

The quasi physical strategy is used to reduce the repetition coverage rate of PSO algorithm in [20], and improves the coverage performance of WSN to some extent. Owing to the simple displacement model and easily control parameters setting, the QPSO algorithm has stronger global optimization ability. The quasi physical strategy in QPSO algorithm has been investigated in our previous work [21]. Firstly, two quasi physical influence factors are introduced in the QPSO position evolution equation to accelerate the convergence speed. The improved QPSO evolution equation can be written as

$$Q(t+1) = X(t) \pm \beta \,|\, P_{avg}(t) - Q(t) \,|\, \ln(\frac{1}{u}) + rand \times \sum_k f_{ik} + rand \times \sum_j f_{ij} \quad . \tag{13}$$

where *rand* is a random number between (0, 1).

Next, based on the idea of “common prosperity” [19, 22], a dynamic balancing strategy is proposed to adjust the sensing radius of WSN nodes. The strategy aims to reduce network coverage redundancy and network energy consumption, also achieve energy-saving optimization coverage. Because each node consumes different energy in WSN, some nodes with excessive energy consumption will prematurely fail than other nodes. Therefore, when the energy consumption of each node tends to be consistent, it will greatly reduce the energy consumption of the whole network and prolong the network lifetime. In the M neighbor nodes of node i, the minimum energy consumption can be expressed as

$$E_{i\min} = \min\{r_{i1}^2, r_{i2}^2, ..., r_{im}^2\} . \quad \textbf{(14)}$$

The average energy consumption of M neighbor nodes is

$$E_{imean} = \frac{1}{m}\sum_{j=1}^{m} r_{ij}^2 . \quad \textbf{(15)}$$

Then the target energy consumption of node i can be written as

$$E_{ibal} = \mu_1 E_{i\min} + \mu_2 E_{imean} . \quad \textbf{(16)}$$

where μ_1, μ_2 is the weight parameter, and $\mu_1+\mu_2=1$.

When the energy consumption of node i is greater than (or less than) its target energy consumption E_{ibal}, it reduces (or increases) energy consumption according to the following Equation (17).

$$E_{inew} = \begin{cases} E_i - \lambda E_{ibal} & E_i > E_{ibal} \\ E_i + \lambda E_{ibal} & E_i \le E_{ibal} \end{cases} . \quad \textbf{(17)}$$

where λ is the radius acceleration factor, between (0, 1). Therefore, the new sensing radius of node i is

$$r_{inew} = \sqrt{E_{inew}} . \quad \textbf{(18)}$$

For a single WSN node, its energy consumption can be reduced by smaller sensing radius. But for overall network, not that the smaller sensing radius, the smaller the energy consumption. In applications, with the decreasing of sensing radius, the number of communications between nodes will increase, which will bring energy load for the network. Therefore, the reasonable sensing radius is very important for WSN coverage performance. In WSN, each node constantly adjusts its sensing radius by Equation (18), and the network will achieve energy balance after repeated iterations. The energy saving optimization algorithm in WSN is described as follows.

Step 1. Initialize the population, and set the number of particles, N. Assume each particle is D dimension, randomly generate N initial positions, and calculate the initial coverage rate of each particle.

Step 2. The location of each particle is updated and the coverage rate is calculated.

Step 3. If the current coverage rate of the particle is better than the individual history value ever experienced, the historical optimal position will be replaced by the current fitness.

Step 4. Find the global optimal value P_g from each particle's individual optimal value P_i.

Step 5. Judge whether the target node is completely covered, if not, the quasi gravitation is in the consideration, and if has been covered, the quasi coulomb force falls into consideration.

Step 6. Adjust the sensing radius dynamically.

Step 7. Judge whether the number of iterations is exceeded, if not, repeat step 2-6 until the end condition is met, otherwise, terminates the process.

5 Simulation Results

5.1 Environment and Parameters

Simulation experiment is carried out in MATLAB 2010. Suppose that the monitoring area is a square area of 20m×20m and disperse the region into a grid with a spacing of 2m, which forms 121 grid points. When the network coverage and energy consumption are simulated, the algorithm performs 100 times and takes its average value. For convenience, we will present the coverage optimization algorithm as the improved QPSO algorithm. It is assumed that the initial sensing radius of each node r=2.5m, communication radius R=5m. The WSN nodes randomly generated in the monitoring area are shown in Fig. 2. In the figure, "*" represents the initial position of the node, and the circle represents the coverage area of the node. Simulation parameter settings are illustrated in Table 1.

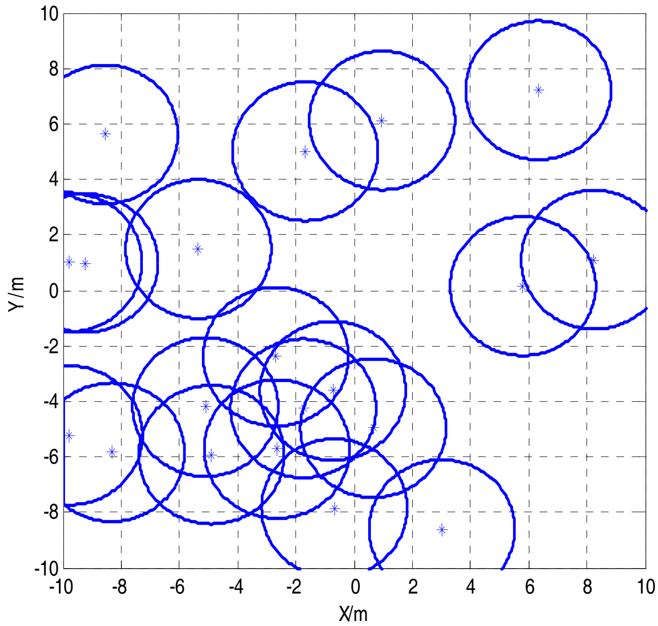


Fig. 2. The initial coverage of WSN nodes

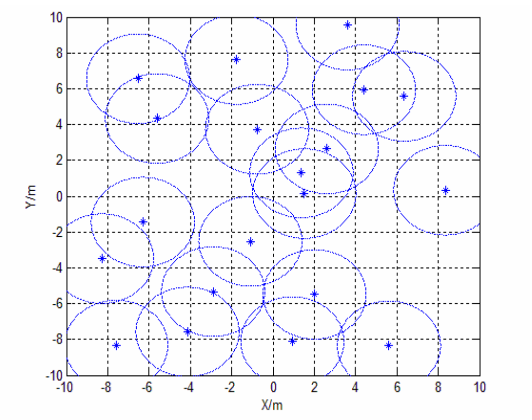
Table 1. Simulation parameters settings

Parameter	Values
Monitoring area	20m×20m
Number of nodes	20
Population size	20
Number of iterations	400
Initial sensing radius	2.5m
Range of sensing radius	[2m, 3.5m]

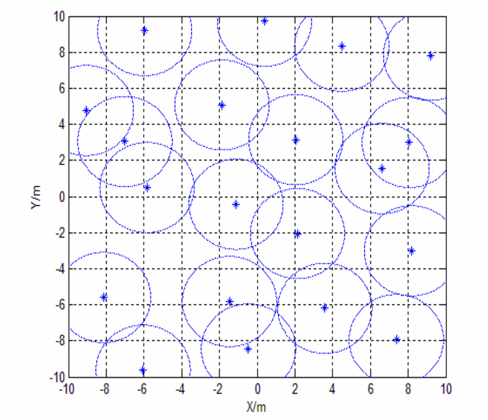
5.2 Coverage Comparison

Fig. 3(a)-Fig. 3(d) give the WSN node distributions for the PSO, QPSO, improved PSO and improved QPSO algorithm. From Fig. 2, Fig. 3(a) and Fig. 3(b), we can see that, the node distribution has some improvement after the implementation of PSO and QPSO algorithms, compared with the initial distribution. However, the node distribution is uneven, and there are still a lot of coverage blind area and repetition coverage area. Moreover, from Fig. 3(c) and Fig. 3(d), it is observed that the node distribution of improved PSO and improved QPSO algorithm is more uniform, coverage blind area and repetition coverage area are relatively small. Also, it can be seen that the node distribution of improved QPSO algorithm is better than that of the improved PSO algorithm.

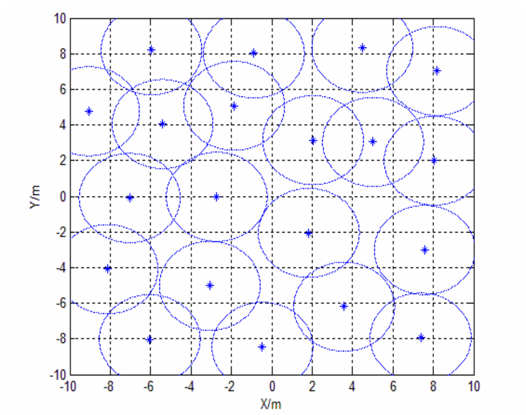
The network coverage comparison of the above 4 algorithms is given in Fig. 4. It can be seen that, when PSO algorithm converges to a stable coverage rate of 69.3%, the number of iterations is 250 times, while the QPSO algorithm converges to a stable coverage rate of 73.9% with the iteration number of 200 times. It shows that the global search ability of QPSO algorithm is better than PSO algorithm. Also, it is observed that the steady-state coverage rate is 79.2% for the improved PSO algorithm, increased by 9.9% and 5.3% compared to PSO and QPSO algorithms, respectively. This is because the quasi gravity and the quasi coulomb force factors can improve the network coverage and optimize the coverage effect. Besides, we can see that the coverage rate is 83.9% for the improved QPSO algorithm, increased by 14.6%, 10% and 4.7% compared to PSO, QPSO, and improved PSO algorithms, respectively. Therefore, it comes the conclusion that the improved QPSO algorithm has the faster convergence speed and better coverage performance.



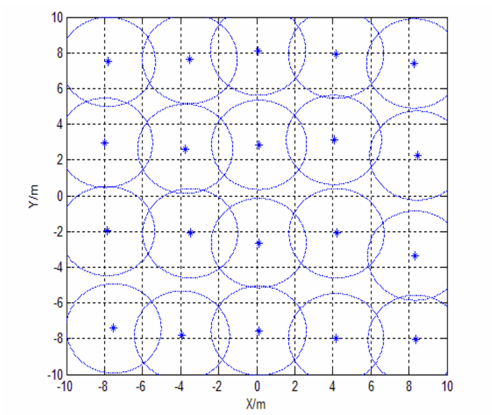
(a) PSO



(b) QPSO



(c) Improved PSO



(d) Improved QPSO

Fig. 3. Node distribution for different algorithms

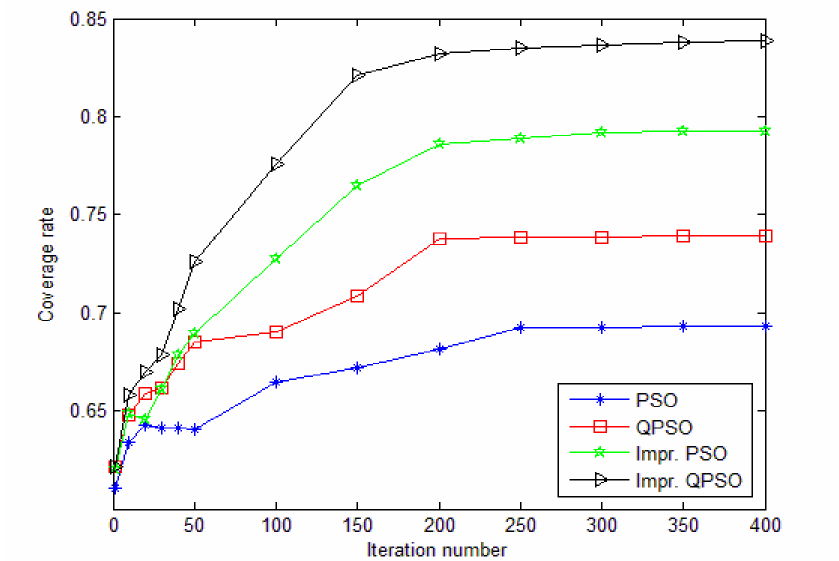


Fig. 4. Network coverage comparison

5.3 Influence of Weighting Parameters on WSN Energy Consumption

Assume the node sensing radius is the range of [2m, 3.5m], the radius acceleration factor λ=0.1, and the iteration number of 50, the impact of the weight parameter μ_1 on WSN energy consumption is illustrated in Fig. 5. It is shown that the energy consumption reduces rapidly, and finally tends to a stable value. Also, it can be seen that when μ_1 is in the range of (0.1, 1), the network has smaller energy consumption in stable state than the range of (0, 0.1). It is concluded that the parameter μ_1 in QPSO algorithm should be limited in the range of (0.1, 1), considering the reduction of energy consumption.

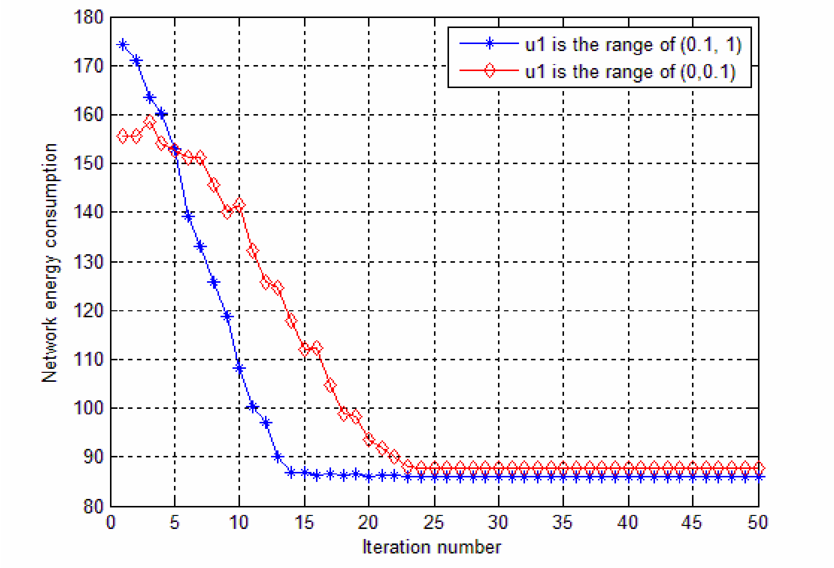


Fig. 5. WSN energy consumption with μ_1

Fig. 6 gives the network energy consumption with λ. It is shown that the network energy consumption decreases with λ decreasing in the stable state. Table 2 shows the relationship between the number of iterations and the energy consumption with different λ in the stable state.

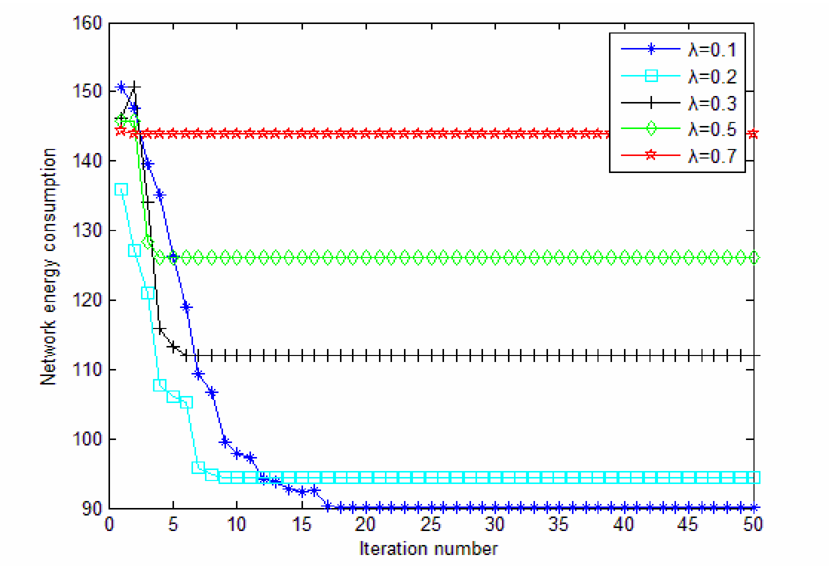


Fig. 6. WSN energy consumption with λ

Table 2. Network Energy Consumption and Number of Iterations with λ

λ	Initial energy consumption	Iteration number in stable state	Energy consumption in stable state
0.1	150.71	18	90.11
0.2	135.89	9	94.34
0.3	146.20	6	112.06
0.5	145.74	4	126.04
0.7	144.27	2	143.94

5.4 Influence of Sensing Radius on WSN Coverage and Energy Consumption

In this section we analyze the impact of node sensing radius on WSN coverage and energy consumption, shown in Fig. 7 and Fig. 8. Assume λ=0.1, and μ_1 is in the range of (0.1, 1). Simulation parameter and values see Table 1.

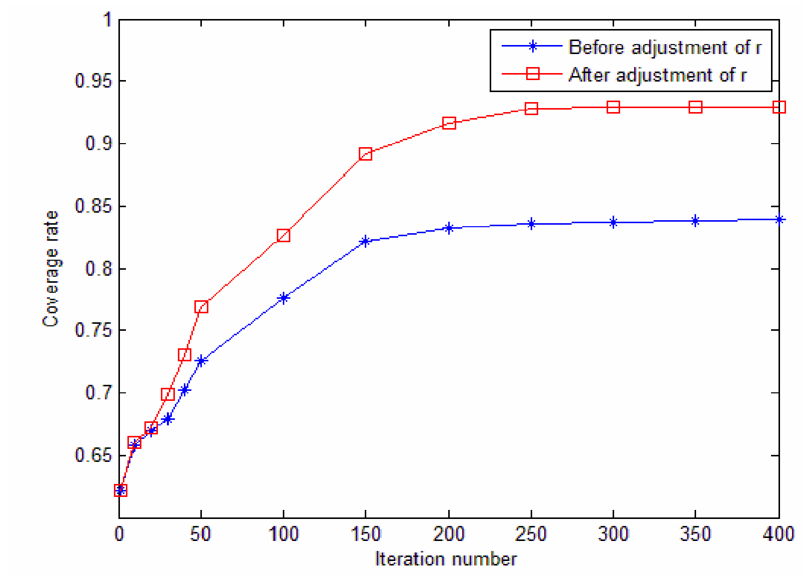


Fig. 7. Effect of sensing radius on WSN coverage

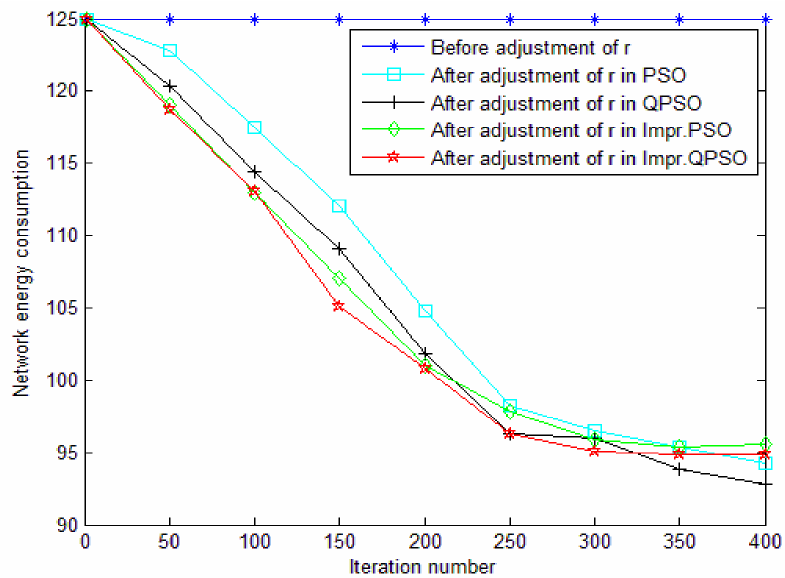


Fig. 8. Effect of sensing radius on WSN energy consumption

From Fig. 7, it can be seen that the improved QPSO algorithm coverage rate is 92.9% after the adjustment of sensing radius *r*, increased by 9% compared to no adjustment of *r*. Also, it is observed that when the same coverage rate is achieved, the improved QPSO has faster convergence speed. It is because that, by adjusting the sensing radius dynamically, the improved QPSO algorithm can avoid the network redundancy and improve the coverage performance.

Fig. 8 shows the WSN energy consumption comparisons after the adjustment of sensing radius *r*. We can see that the WSN energy consumption is much lower after adjustment of sensing radius *r*. However, the energy consumption difference is not obvious in four algorithms.

6 Conclusion

This paper introduces an optimization node deployment scheme in WSN, which is based on the adjustment of node sensing radius to improve area coverage and network lifetime. A comparison between different algorithms commonly used for network coverage is provided. Simulation results show that the proposed scheme increases area coverage and reduces the amount of energy consumed in WSN. For future work, the different mobility model of nodes and clustering deployment strategy are considered to improve network lifetime. In addition, future research is considering the direction coverage problem in WSN.

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