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Research article

Wireless Sensor Network coverage optimization based on Yin–Yang pigeon-inspired optimization algorithm for Internet of Things

Jianghao Yin [a], Na Deng [a,*], Jindan Zhang [b]

[a] School of Computer science, Hubei University of Technology, Wuhan, Hubei, China
[b] Xianyang Vocational Technical College, Xi'an, Shanxi, China

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ABSTRACT

As an important technology of Internet of Things (IoT), wireless sensor network (WSN) has the problem of low coverage caused by uneven nodes distribution. Aiming at the problem, a WSN coverage optimization method based on the Yin–Yang pigeon-inspired optimization algorithm (Yin–YangPIO) is proposed. Firstly, the good point set is introduced into initialization phase which makes pigeon population more evenly distributed in the solution space; then, Yin–Yang-pair optimization algorithm (YYPO) and pigeon-inspired optimization algorithm (PIO) are combined, and different strategies are used in the map and compass operator and the landmark operator to improve the optimization ability; later on, the opposition-based learning is added to PIO to expand the search range; finally, several functions are selected to prove the optimization ability of the Yin–YangPIO. Through three sets of WSN coverage optimization experiments with different parameters, the effectiveness of the proposed method in WSN coverage optimization is demonstrated.

1. Introduction

The rapid development of the Internet of Things (IoT) has brought great convenience to people [1–3]. With the emergence of fifth-generation of mobile telecommunications technology (5G), it will further promote the development of IoT technology [4]. Wireless Sensor Network (WSN) can be considered as a fundamental part of the IoT [5], which is a network composed of multiple resource-constrained sensor nodes [6]. And the WSN is widely used in the fields of healthcare, military, and weather monitoring [7]. In order to achieve full coverage of the monitoring area, a large number of nodes are usually deployed, which is not only costly, but also easily leads to communication conflicts. How to optimize the deployment of mobile nodes and cover a larger area with fewer nodes has become a hotspot in wireless sensor network research [8].

At present, the research on WSN coverage problem mainly focuses on the dynamic network coverage optimization based on the binary coverage model, and two types of dynamic network coverage methods have been formed [9]. One is the coverage optimization based on geometric figures. For example, Sung and Yang [10] put forward a Voronoi-based network coverage optimization method, but this kind of method has complex theoretical and computational problems. The other one is based on intelligent algorithms, which avoid complex theoretical derivation, such as particle swarm optimization (PSO) [11], whale optimization algorithm (WOA) [12], and firefly algorithm (FA) [13]. But this kind of method has the problem that it is likely to trap in local optimum and premature.

Pigeon-inspired optimization algorithm (PIO) is a bionic intelligent optimization algorithm with the advantages of simple structure, easy understanding, and strong global search ability. At present, it has been applied to unmanned aerial vehicle (UAV) formation [14], proportional integral derivative (PID) parameter setting [15], image segmentation [16], and other fields. Therefore,

* Corresponding author.
E-mail addresses: yinjianghao@hbut.edu.cn (J. Yin), iamdengna@163.com (N. Deng), zhangjindan83@163.com (J. Zhang).

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in the light of the above problems, a WSN coverage optimization method based on Yin–YangPIO is put forward. The main contributions of this paper are: 1. An improved PIO is proposed which is named Yin–YangPIO. The algorithm combines the Yin–Yang-pair optimization algorithm (YYPO) with the PIO, then adds the good point set and opposition-based learning. 2. We propose a WSN coverage optimization method based on the Yin–YangPIO. By comparing with some existing studies, the effectiveness of the WSN coverage optimization based on Yin–YangPIO is further verified.

The rest of this paper is organized as follows: In Section 2, related work in the field of PIO, YYPO and WSN are presented; in Section 3, the standard PIO and YYPO are presented, then WSN coverage model is set up; Section 4 demonstrates the method proposed in this paper; Section 5 tests the improved algorithm on standard functions and conducts a comparison experiment with existing research on WSN coverage optimization; Section 6 draws a conclusion on the whole research and the future work is put forward.

2. Related work

2.1. Related work on pigeon-inspired optimization algorithm

PIO was first put forward by Duan and Qiao [17] in 2014. Although PIO is strong in global search, it still has the problem of premature and easy to trap in the local optimal solution. Many scholars have proposed improvement methods. Duan and Yang [18] proposed a PIO based on Cauchy mutation, adding Cauchy mutation to PIO, then applied the algorithm to large civil aircraft receding horizon control. Dou and Duan [19] proposed a PIO based on Levy flight which was utilizing in controlling parameter optimization of the automatic carrier landing system. Tao and Li [20] proposed a crossed PIO with cognitive factor. In this algorithm, two operators were firstly cross-operated, and then a nonlinear increasing cognitive factor was introduced into map and compass operator, at the same time a compression factor was added to landmark operator, which improved the algorithm accuracy. Wang et al. [21] proposed a cooperative PIO with dynamic distance threshold, in which a distance threshold was added to make the population multifarious, and the algorithm was applied to the image threshold segmentation problem. Xia et al. [22] put forward an improved PIO of fuzzy variation operator. In this method, inspired by the differential evolution algorithm, the fuzzy variation operator was introduced to improve the position update formula, thereby improving the search ability.

2.2. Related work on Yin–Yang-pair optimization algorithm

The YYPO is a newfashioned intelligent optimization algorithm that was first put forward by Punnathanam and Kotecha [23]. And the YYPO is not a simulation of any specific mechanism, but is expected to achieve an equilibrium in search range from the perspective of Yin–Yang balance. However, it is easy to trap in local optimum. Xu et al. [24] put forward a YYPO based on chaos search and intricate operator. In this algorithm, chaos search was introduced, and opposition-based learning strategy was added to perform a centralized search for the reverse solution of the current solution, which improved the optimization ability. Heidari et al. [25] combined the PSO with the YYPO, applied it to the uncapacitated warehouse location (UWL) problems, and achieved good optimization results; Wang et al. [26] proposed a seagull optimization algorithm (SOA) combined with YYPO, and proved that the performance of the algorithm had been enhanced. Xu et al. [27] proposed a novel YYPO based on the wavelet elite solutions learning and multi-angle search. Firstly, the wavelet elite solution learning strategy is introduced into the algorithm to take advantage of the elite solution's information, and then the search angle is introduced into the update equation to strengthen the search of the solution space.

2.3. Related work on WSN coverage optimization

At present, there have been some researches on WSN coverage optimization based on metaheuristic algorithm. Wu et al. [28] put forward a coverage optimization method based on the improved adaptive PSO. Firstly, the method improved inertia weight by adding evolution factor and aggregation factor; and then the collision resilient strategy is introduced in the algorithm iteration process to ensure make the particle swarm multifarious. Kong et al. [29] proposed a WSN coverage improvement method based on the enhanced PSO, which introduced inertia coefficient and mutation operator to accelerate the convergence and make the population multifarious, thereby improving the network coverage. Lu et al. [30] proposed a WSN coverage optimization method based on FA, in which the positions of two nodes are replaced at a time to improve the network coverage. Huang et al. [31] proposed a WSN coverage optimization method based on artificial fish swarm algorithm (AFSA). Simulation experiments proved that ASFA improved the coverage of wireless sensor network nodes. Although these intelligent algorithms enhance the coverage ratio of the network to a certain extent, they still have some shortcomings, such as the problem of precociousness and low search accuracy when using PSO and FA. When using AFSA, the parameter configuration is very critical, and unreasonable parameter configuration will make convergence slow. Therefore, a WSN coverage optimization method based on the Yin–YangPIO is put forward, so as to improve the WSN coverage ratio. This method combines PIO with YYPO to enhance the optimization ability of PIO, and uses the good point set instead of random initialization to make the population distribution more uniform, finally introduce the opposition-based learning to make the population multifarious.

3. Preliminary

3.1. Pigeon-inspired optimization algorithm

The PIO is inspired by the activities of pigeons when they homing [17]. When pigeons homing, they usually use three tools: magnetic field, sun, and landmarks. When the pigeon is some distance from the target place, it will use the magnetic field and the sun to draw a map in the brain and constantly adjust the direction. When the pigeon is closer to the target place, it will use the familiar landmark to move to the target place. If there is no familiar landmark, the pigeon will follow the familiar pigeon. According to these characteristics of pigeons, the PIO designs two kinds of operators: map and compass operator and landmark operator.

Map and compass operator: in the D-dimensional solution space, the speed of the ith pigeon is updated according to Formula (1), and the position is updated according to Formula (2).

$$V_i(t) = V_i(t-1) \cdot e^{-Rt} + \mathrm{rand} \cdot \left(X_g - X_i(t-1)\right) \tag{1}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{2}$$

where $V_i\,(t)$ is the speed of the ith pigeon in the tth generation, $V_i\,(t-1)$ is the speed of the ith pigeon in the $(t-1)$-th generation, R is the map and compass factor, $rand$ is a random number in range of $[0,1]$, X_g is the global optimal position, $X_i\,(t)$ is the position of the ith pigeon in the tth generation, $X_i\,(t-1)$ is the position of the ith pigeon in the $(t-1)$-th generation.

Landmark operator: each iteration update will be reduced by half according to Formula (3), and the individuals which have poor fitness will be sifted out. Then the central position $X_c\,(t)$ of the pigeons is calculated according to Formula (4). The position update refers to Formula (5):

$$N_p(t) = \frac{N_p(t-1)}{2} \tag{3}$$

$$X_c(t) = \frac{\sum X_i(t) \cdot \text{ fitness } \left(X_i(t)\right)}{N_p \cdot \sum \text{ fitness } \left(X_i(t)\right)} \tag{4}$$

$$X_i(t) = X_i(t-1) + \mathrm{rand} \cdot \left(X_c(t) - X_i(t-1)\right) \tag{5}$$

where $N_p\,(t)$ is the number of pigeons in the tth generation, $N_p\,(t-1)$ is the number of pigeons in the $(t-1)$-th generation, $X_i\,(t)$ is the position of the ith pigeon in the tth generation, $X_i\,(t-1)$ is the position of the ith pigeon in the $(t-1)$-th generation, and $fitness()$ is the fitness function.

3.2. Yin–Yang-pair optimization algorithm

The YYPO is a metaheuristic algorithm that integrates the duality thought that exists widely in the universe [23]. In this algorithm, all variables will be normalized between 0 and 1. The algorithm is based on the exchange mechanism of two points P_1 and P_2 to achieve optimization, where P_1 focuses on local search, and P_2 focuses on global search. P_1 and P_2 serve as the centers of hyperspheres with δ_1 and δ_2 as radii, respectively. δ_1 and δ_2 have periodic decreasing and increasing trends, respectively. The algorithm will go through splitting stage and archive stage. Before the splitting stage, the archive updates I will be chosen between the integer I_{min} and the integer I_{max} (I_{min} and I_{max} are archive updates minimum and archive updates maximum respectively). P_1 and P_2 are updated with the $2I$ points saved in the archive every time they go through I splitting stages.

Splitting stage:

Assuming that the dimension is D, $2D$ new points will be generated in the splitting stage, and only one point will be split at a time, denoted as point P, and the update of point P will be generated in the following two ways:

One-way splitting: The $2D$ identical copy will be stored in S, which is a $2D \times D$ matrix, and each point in S is updated according to Formula (6):

$$\begin{aligned} &S_j^j = S^j + r\delta \quad \text{and} \\ &S_{D+j}^j = S^j - r\delta, \quad \text{where} \quad j = 1,2,3 \dots D \end{aligned} \tag{6}$$

where the subscript represents the point number, the superscript represents the decision variable number being modified, r represents a random number which is in range of $[0,1]$, and δ represents the search radius.

D-way splitting: Same as one-way splitting, store $2D$ identical copies of P in S. Unlike one-way splitting, where only one variable is modified at each point, in D-way splitting, all variables at each point will be changed. At this stage, a binary matrix B of size $2D \times D$ will be generated, and the points in S will be updated according to Formula (7):

$$\begin{aligned} &S_k^j = S^j + r(\delta/\sqrt{2}) \text{ if } B_k^j = 1, \\ &S_k^j = S^j - r(\delta/\sqrt{2}) \text{ else}, \\ &\text{where} \quad k = 1,2,3 \dots 2D \quad \text{and} \quad j = 1,2,3 \dots D \end{aligned} \tag{7}$$

The meaning of the variables in the formula is the same as above.

In the generated $2D$ new solutions, the point with the best fitness is selected to take place of the point P. Regardless of whether the best fitness in the new solution is greater than that of the point P, the point with the best fitness will be used to take place of point P.

Archive stage:

Firstly, we select the point with the best fitness from the archive. If the point is better than P_1, the two points exchange values, and then continue to select the point with the best fitness from the remaining points in the archive, if the point is better than P_2, then exchange the values of the two points. Finally, the archive set will be cleared and the archive updates I will be revalued.

At this stage, δ_1 and δ_2 will be adjusted according to Formula (8) and Formula (9):

$$\delta_1 = \delta_1 - \left(\delta_1/\alpha\right) \tag{8}$$

$$\delta_2 = \delta_2 + \left(\delta_2/\alpha\right) \tag{9}$$

where δ_1 is the search radius of point P_1, δ_2 is the search radius of point P_2, and α is the expansion/contraction factor.

3.3. WSN coverage model

Assuming that the monitoring area is a two-dimensional target plane, N sensor nodes are placed in the area, the sensing radius of each node is r, and the communication radius is R. Generally, the communication radius is set as $R = 2r$ to maintain the connectivity of the network. The sensor nodes set can be expressed as Formula (10):

$$G = \left\{g_1, g_2, g_3, \ldots, g_N\right\} \tag{10}$$

where the coordinates of each sensor node g_i are marked as $\left(a_i, b_i\right)$. The monitoring area can be discretized into $m \times n$ pixel points, and the pixel point is F, the coordinate of point F is $\left(x_F, y_F\right)$, and the distance calculation formula from point F to each sensor node g_i is represented as Formula (11):

$$d\left(g_i, F\right) = \sqrt{\left(x_F - a_i\right)^2 + \left(y_F - b_i\right)^2} \tag{11}$$

where $d\left(g_i, F\right)$ is the distance from point F to sensor node g_i. In this paper, the sensor perception model uses the Boolean perception model, and the calculation method of the probability of being perceived by the sensor node g_i at the pixel point F is as shown in Formula (12):

$$p\left(g_i, F\right) = \begin{cases} 1 & d\left(g_i, F\right) \leqslant r \\ 0 & d\left(g_i, F\right) > r \end{cases} \tag{12}$$

where $p\left(g_i, F\right)$ is the probability of being perceived by the sensor node g_i at the pixel point F, and r is the sensing radius.

In practical situations, each pixel can be perceived by more than one sensor node, and the joint probability of the pixel F being perceived by the node set G is shown in Formula (13):

$$p(G, F) = 1 - \prod_{g_i \in G} \left[\left(1 - p\left(g_i, F\right)\right]\right. \tag{13}$$

The coverage ratio of the sensor node set to the monitoring area is shown in Formula (14):

$$\mathrm{COV}(G) = \frac{\sum_{F \in m \times n} p(G, F)}{m \times n} \tag{14}$$

where $p(G, F)$ is the joint probability that the pixel point F is perceived by the node set G, and $m \times n$ is the total number of pixels.

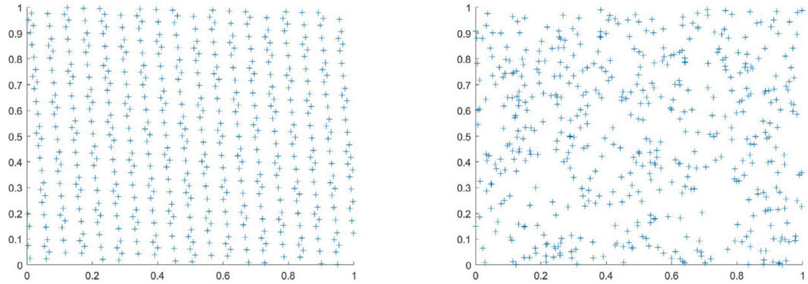
4. Proposed method

4.1. Good point set

In the traditional PIO, the initial population is randomly generated, which makes the individuals not evenly distributed in the solution space. A well-distributed pigeon population will enhance the search ability, so this paper will enhance the initialization stage with good point set. The theory of good point set was firstly proposed by Hua Luogeng [32]. Zhang et al. [33] used good point set to enhance the genetic algorithm (GA). The enhanced GA has greater performance than before. We refer to literature [34]: G_d represents the unit cube in the d-dimensional Euclidean space, let $r \in G_d$, if

$$P_n(k) = \left\{\left(\left\{r_1^{(n)} \cdot k\right\}, \left\{r_2^{(n)} \cdot k\right\}, \ldots \left\{r_s^{(n)} \cdot k\right\}\right), 1 \le k \le n\right\} \tag{15}$$

The deviation of Formula (15) is $\varphi(n)$, and $\varphi(n)$ satisfies $\varphi(n) = C(r, \varepsilon) n^{-1+\varepsilon}$, where n is the number of nodes, $\left\{r_d^{(n)} \cdot k\right\}$ means taking the fractional part, $C(r, \varepsilon) n^{-1+\varepsilon}$ is a constant only related to r and ε, and ε is any positive number, then $P_n(k)$ is good point



(a) Using good point set initialization (b) Using random initialization

Fig. 1. Good point set initialization versus random initialization.

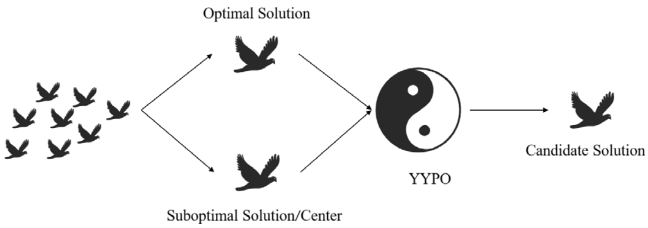


Fig. 2. The schematic diagram of PIO adding Yin–Yang improvement strategy.

set, r is the good point. Take $r = \{2\cos(2\pi k/p), 1 \leq k \leq s\}$, p is the smallest prime number satisfying $(p-3)/2 \geq s$. The improved initialization method is shown in Formula (16):

$$x_i(j) = \left(ub_j - lb_j\right) \cdot \left\{ r_j^{(i)} \cdot k \right\} + lb_j \tag{16}$$

where ub_j is the upper bound of the jth dimension, and lb_j is the lower bound of the jth dimension.

Fig. 1 shows 500 individuals generated in the range of $[0,1]$ using the good point set and the random method. The result of utilizing good point set is displayed in Fig. 1(a) and the result of utilizing the random method is displayed in Fig. 1(b). As seen from Fig. 1 that the pigeon population distribution is more uniform when the good point set is used for initialization.

4.2. Yin-Yang improvement strategy

In map and compass operator, the individuals in population will approach the pigeon which has the best fitness, so the position of the optimal solution has a great influence on the early search. Heidari et al. [25] combined PSO with YYPO and Wang et al. [26] combined SOA with YYPO. The optimization ability of both algorithms has been improved. Inspired by the researches above, this paper combines YYPO with PIO to enhance the optimal solution's quality.

Before starting the map and compass operators each time, take the best and second-best points of the current population as the initial points P_1 and P_2 of YYPO. Then enter the splitting stage and archive stage, make a comparison between the result and the best individual of the current population. If the candidate solution is greater than the best individual, the candidate solution is used to replace the best individual of the current population.

In the landmark operator, each iteration will calculate the center position of the pigeon population, and the quality of the center position will affect the search ability of the algorithm later. After each calculation of the center position, the center position and the optimal pigeon are used as the initial points P_1 and P_2 of YYPO. After that enter the splitting stage and archive stage, make a comparison between the result and the center position. If the candidate solution is greater than the center position, the candidate solution is used to replace the center position of the current population.

The schematic diagram of PIO adding Yin–Yang improvement strategy is presented in Fig. 2.

4.3. Opposition-based learning

In the PIO, if the points in the current population are close to the optimal point, the algorithm may quickly converge, but if the individuals in the current population are a long way from the optimal position, the algorithm is likely to trap in a local optimal solution. Finding better candidate solutions from opposite directions in population at the same time can effectively solve the current problem [35]. This is exactly the idea of opposition-based learning, which was proposed by Tizhoosh in 2005 [36]. Currently, many

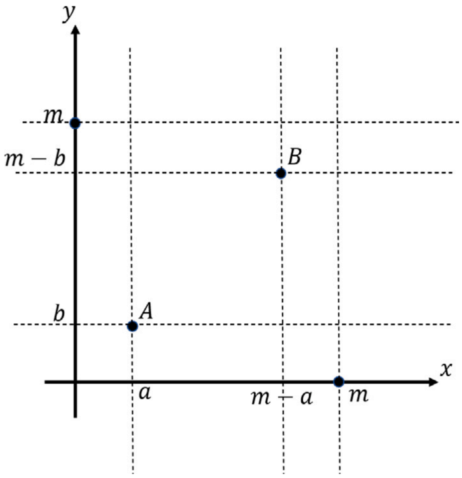


Fig. 3. Diagram of opposite solution.

methods have been enhanced by opposition-based learning, such as reinforcement learning, artificial neural networks, intelligent algorithms, etc. [37].

Assuming that an n-dimensional point is $Q\left(x_1, x_2, \ldots, x_n\right)$, then the opposite solution of this point is $Q'\left(x_1', x_2', \ldots, x_n'\right)$. The calculation method of Q' is shown in Formula (17):

$$x_j' = a_j + b_j - x_j \tag{17}$$

where x_j' is the jth dimension variable of point Q', a_j is the maximum value of the jth dimension in the current population, b_j is the minimum value of the jth dimension in the current population, and x_j is the jth dimension variable of point Q.

As shown in Fig. 3, it is assumed that when using PIO to cope with a two-dimensional function, the maximum value in each dimension is m, the minimum value is 0, and the original point is $A(a, b)$, where $0 \leq a \leq b \leq m$, then the opposite solution of this point is point $B(m-a, m-b)$.

The pigeon population conducts a global search in map and compass operator. At this stage, the pigeons need to be able to search in a wider range. For this reason, this paper introduces opposition-based learning at this stage. After the position of the pigeon is updated, the opposite solution of the individuals in the population is calculated at the same time, the fitness of the original population and the opposite population are compared, and the individuals with better fitness are retained in the new population.

4.4. The process of Yin–YangPIO

The flow diagram of Yin–YangPIO is shown in Fig. 4:

Step 1: Initialize the pigeon population utilizing good point set, and calculate the fitness of the population.

Step 2: The individuals with the best fitness and the second-best in the population are put into YYPO as the initial values of P_1 and P_2.

Step 3: Update the population position according to Formula (1) and Formula (2).

Step 4: Using the opposition-based learning strategy, individuals with better fitness are retained.

Step 5: If t is less than Nc_1, jump to Step 2, otherwise jump to Step 6.

Step 6: Reduce the population according to Formula (3).

Step 7: Solve for the center position of the population according to Formula (4). The center position and individuals with the best fitness in the population are put into YYPO as the initial values of P_1 and P_2.

Step 8: Update the position of the population according to Formula (5).

Step 9: If t is less than Nc_2, go to Step 6, otherwise the program ends.

5. Experiment and analysis

5.1. Algorithm performance analysis

In order to verify the performance of the Yin–YangPIO algorithm proposed in this paper, five representative standard functions are selected for testing, f_1: Sphere Function, f_2: Rosenbrock Function, f_3: Levy Function, f_4: Schwefel Function, f_5: Levy Function N.13. These five test functions can be divided into two groups, f_1, f_2 are unimodal functions, which can detect the convergence speed of the algorithm, f_3, f_4, f_5 are multimodal functions, with many local optimal values, which can detect the ability of jumping

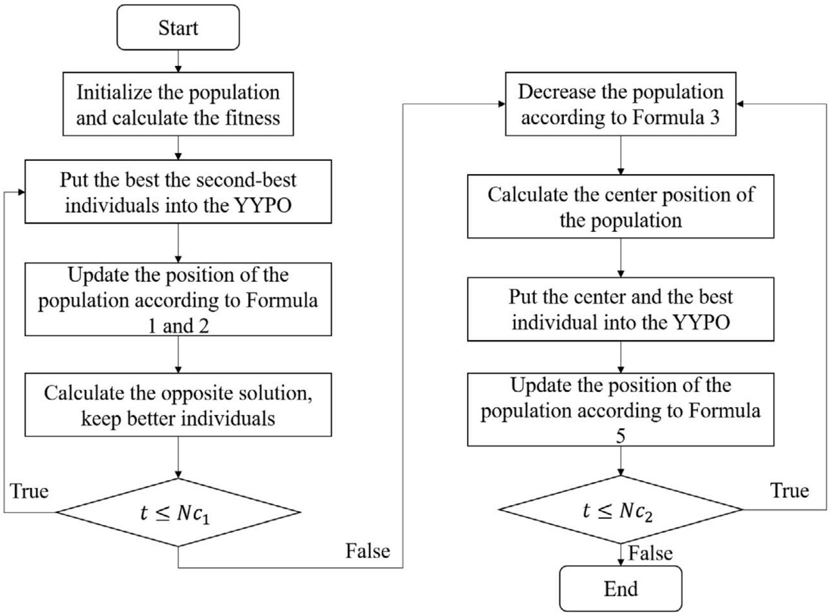


Fig. 4. The flowchart of Yin–YangPIO.

Table 1
Test functions.

Function	x^*	$f(x^*)$	Range	Dimension
$f1$	[0, 0, 0..., 0]	0	[−100, 100]	30
$f2$	[1, 1, 1..., 1]	0	[−2.048, 2.048]	30
$f3$	[1, 1, 1, … , 1]	0	[−10, 10]	30
$f4$	[420.96, … , 420.96]	0	[−500, 500]	30
$f5$	[1, 1]	0	[−10, 10]	2

out of the local optimal point. The specific information of the function is shown in Table 1. x^* is the theoretical minimum point of the function, and $f(x^*)$ is the theoretical minimum value of the function.

This paper compares Yin–YangPIO with PIO, YYPO and PSO. For Yin–YangPIO, the number of populations N is set as 50, the iterative maximum $IterMax$ is set as 500, the iterative maximum of the map and compass operator Nc_1 is set as 350, and the iterative maximum of the landmark operator Nc_2 is set as 150. The parameter settings of the PIO are the same as those of Yin–YangPIO; For YYPO, the iterative maximum is set as 500, the maximum archive updates I_{max} is set as 4, the maximum archive updates I_{min} is set as 2, the expansion/contraction factor α is set as 10, and the search radius δ_1 and δ_2 are set as 0.5. For PSO, the iterative maximum is set as 500, the individual learning factor c_1 is set as 2, the social learning factor c_2 is set as 2, and the inertia weight w is set as 0.9. Each algorithm run independently on MATLAB 2018b for 20 times, and the results are presented in Table 2.

As seen from the Table 2, among the five functions, the minimum value, average value and variance of Yin–YangPIO are the best, indicating that Yin–YangPIO has high optimization accuracy and strong stability. In the experiments of the function f_3 f_4 and f_5, it is proved that Yin–YangPIO has a strong ability of global search and jumping out of the local optimal solution. For function f_4, although YYPO has the same minimum value as Yin–YangPIO, Yin–YangPIO achieves the minimum value in 20 independent experiments, the variance is 0, so it has better stability.

5.2. WSN coverage optimization simulation experiment

5.2.1. Compared with PSO and PIO

To testify the effectiveness of the Yin–YangPIO in WSN coverage optimization problem, we first compare the method proposed in this paper with PSO and PIO. We use Formula (14) as the objective function when solving WSN coverage optimization model. The horizontal and vertical coordinates of the nodes are used as the solution vector. For example, when the number of nodes is 20, the dimension of the solution vector is 40. At the same time, we will also use the coverage efficiency to evaluate the optimization results. In WSN, coverage efficiency is usually the average coverage rate of each sensor, which can reflect the degree of node redundancy. The higher the coverage efficiency, the smaller the redundancy of nodes. The calculation method is as Formula (18):

$$CE = \frac{\bigcup_{i=1,2,\ldots,N} S_i}{\sum_{i=1,2,\ldots,N} S_i} \tag{18}$$

Table 2
Test function optimization results.

Function	Algorithm	Max	Min	Mean	Variance
f_1	PSO	3.03E+00	1.25E+00	2.10E+00	3.27E−01
	YYPO	7.15E−07	6.83E−11	4.33E−08	2.52E−14
	PIO	1.55E−116	1.14E−177	7.75E−118	1.20E−233
	Yin-YangPIO	0.00E+00	0.00E+00	0.00E+00	0.00E+00
f_2	PSO	1.68E+02	3.17E+01	5.09E+01	8.87E+02
	YYPO	7.98E+01	1.94E+01	3.45E+01	3.41E+02
	PIO	2.87E+01	9.21E−02	1.64E+01	1.61E+02
	Yin-YangPIO	3.68E−01	0.00E+00	6.57E−02	1.08E−02
f_3	PSO	8.67E+00	1.67E+00	5.01E+00	4.06E+00
	YYPO	3.40E−03	4.44E−12	4.11E−04	8.56E−07
	PIO	1.36E+00	4.67E−08	1.95E−01	1.69E−01
	Yin-YangPIO	8.30E−09	1.50E−32	4.22E−10	3.44E−18
f_4	PSO	8.34E+03	5.00E+03	6.33E+03	7.32E+05
	YYPO	6.03E+00	3.82E−04	3.03E−01	1.82E+00
	PIO	4.51E+03	1.60E−03	1.98E+03	3.15E+06
	Yin-YangPIO	3.82E−04	3.82E−04	3.82E−04	0.00E+00
f_5	PSO	8.83E−05	5.33E−08	1.44E−05	3.90E−10
	YYPO	1.63E−12	7.61E−16	2.34E−13	2.08E−25
	PIO	3.19E−02	2.32E−07	4.60E−03	7.75E−05
	Yin-YangPIO	3.32E−13	1.35E−31	3.32E−14	1.04E−26

Table 3
Coverage ratio and coverage efficiency comparison.

Method	Coverage ratio	Coverage efficiency
PSO	93.10%	69.67%
PIO	89.29%	68.55%
Yin-YangPIO	99.51%	91.67%

Table 4
Coverage ratio comparison.

Method	Sensing radius		
	13 m	14 m	15 m
PSO	80.26%	86.3%	93.10%
PIO	77.81%	82.26%	89.29%
Yin-YangPIO	91.73%	96.95%	99.51%

where CE is the coverage efficiency, S_i is the coverage area size of the ith node, and N is the number of nodes.

The monitoring area is set as a square area of $100\ \mathrm{m} \times 100\ \mathrm{m}$ in which 20 sensor nodes are distributed. The sensing radius of each sensor node is set as 15 m, the communication radius is set as 30 m, and iterative maximum is set as 80. The first set of experiments uses Yin–YangPIO, PIO, and PSO algorithms for comparison. The parameter settings of the three algorithms refer to Section 5.1. The coverage ratio using each method are presented in Table 3 and Fig. 5.

As seen from the Table 3, Yin–YangPIO has the best optimization effect, with a coverage ratio of 99.51%. This experiment can prove that Yin–YangPIO has a better effect than the standard PIO and PSO algorithms in solving WSN coverage optimization problem. The coverage ratio optimized by Yin–YangPIO is 10.22% higher than that of the PIO, and 6.41% higher than that of PSO. The coverage efficiency of Yin–YangPIO is also the highest, which is 23.12% higher than PIO and 22% higher than PSO. The convergence curve using the three algorithms as shown in Fig. 6:

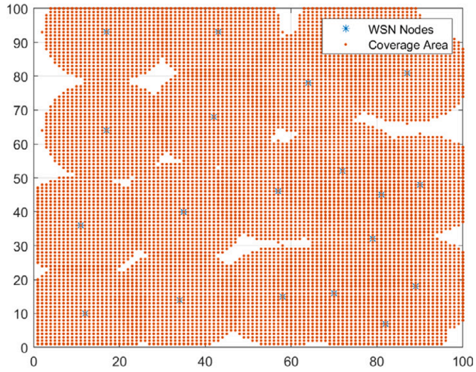
As seen from Fig. 6, the coverage ratio of Yin–YangPIO is 87.12% at the initial time, and the coverage rate has reached 99.51% at the sixth iteration. Compared with PIO and PSO, Yin–YangPIO algorithm has better convergence in solving WSN coverage optimization problem.

Next, in order to explore the optimization under different sensing radius, we do not change other parameters, and set the sensing radius to 13 m, 14 m, and 15 m in turn. The experimental results obtained are shown in the Table 4.

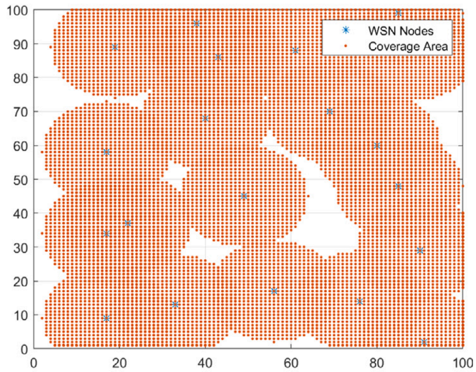
As seen from the Table 4, under different sensing radius, the coverage ratio of using Yin–YangPIO is the highest among the three algorithms, and all reach more than 90%.

5.2.2. Compared with other studies

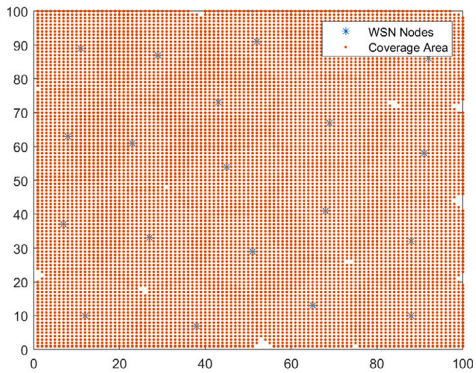
In the second set of experiments, the monitoring area is set as a square area of $100\ \mathrm{m} \times 100\ \mathrm{m}$ in which 30 sensor nodes are distributed. The sensing radius of each sensor node is set as 13 m, the communication radius is set as 26 m, and the iterative maximum is set as 80. The parameter settings of the Yin–YangPIO refer to Section 5.1. The Yin–YangPIO is compared with



(a) PSO



(b) PIO



(c) Yin-YangPIO

Fig. 5. Node coverage distribution diagram.

literature [28], literature [38] and literature [39]. The coverage ratio of literature [38] and literature [39] refers to literature [28]. The coverage ratio using each method are presented in Table 5 and Fig. 7.

As seen from the Table 5, compared with the methods proposed in literature [28], literature [38] and literature [39], YinYangPIO has a certain improvement in WSN coverage ratio.

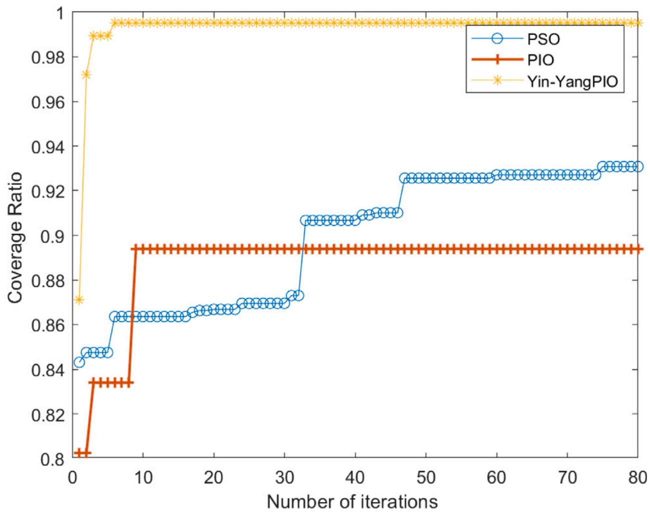


Fig. 6. Convergence curve.

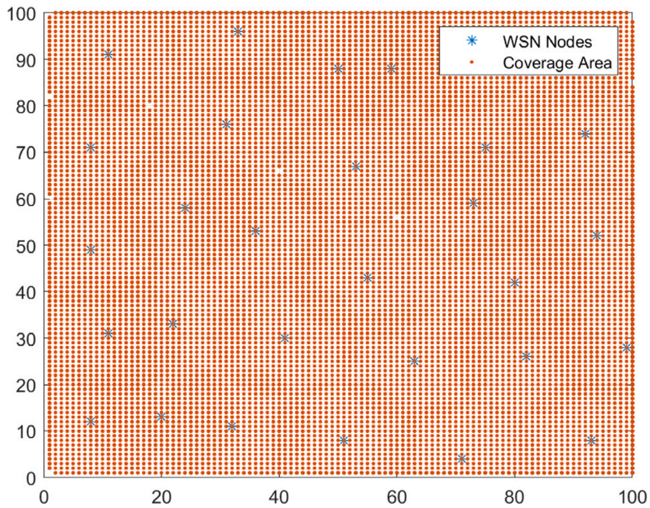


Fig. 7. Node coverage distribution diagram.

Table 5
Coverage ratio comparison.

Method	Coverage ratio
Literature [38]	97%
Literature [39]	94%
Literature [28]	99.80%
Yin-YangPIO	99.90%

In the third set of experiments, the monitoring area is set as a square area of 100 m × 100 m in which 45 sensor nodes are distributed. The sensing radius of each sensor node is set as 10 m, the communication radius is set as 20 m, and the iterative maximum is set as 80. The parameter settings of the Yin–YangPIO refer to Section 5.1. The Yin–YangPIO is compared with the method proposed in literature [40]. The coverage ratio using each method are presented in Table 6 and Fig. 8.

As seen from the Table 6, the optimization results of Yin–YangPIO proposed in this paper have an improvement of more than 2% compared with improved artificial bee colony algorithm using teaching strategy (TABC) proposed in literature [40], and the sensor node coverage is more uniform.

Table 6
Coverage ratio comparison.

Method	Coverage ratio
Literature [40]	96.07%
Yin-YangPIO	98.46%

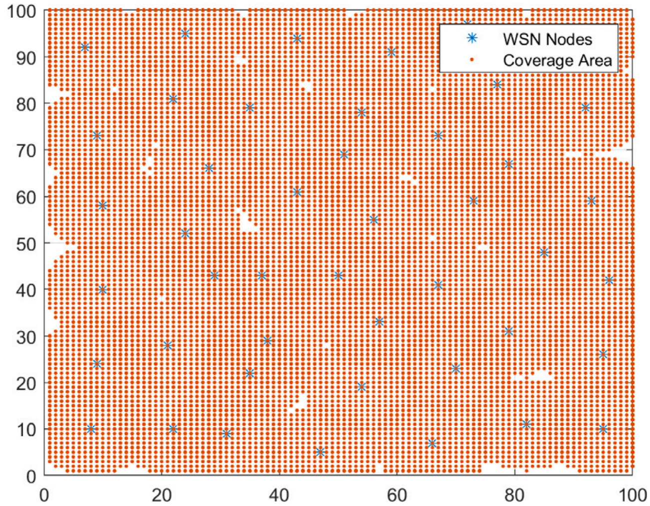


Fig. 8. Node coverage distribution diagram.

6. Conclusion and future work

This paper puts forward a WSN coverage optimization method based on Yin–YangPIO. Firstly, good point set is introduced into the initialization stage to make the pigeon population more uniformly distributed in the solution space. Then, considering that the optimal value of the population in PIO has a leading role in the population, YYPO is combined with PIO so as to enhance the optimal solution and center position. In map and compass operator, the optimal and suboptimal individuals of the population are put into YYPO as P_1 and P_2 for optimization; in the landmark operator, the center of the population and the optimal individuals are put into YYPO as P_1 and P_2 for optimization, thereby enhancing the optimization accuracy. In map and compass operator, the search range should be expanded, and the solution space should be searched as much as possible so as to prevent PIO from trapping in a local optimum. Therefore, opposition-based learning is added to the map and compass operators to improve the diversity of the population. In experiments, first, five standard test functions are selected and the comparison experiments between Yin–YangPIO and PIO, PSO, YYPO are carried out. The experimental results show that Yin–YangPIO has stronger optimization ability and stability than PIO, PSO and YYPO. Three groups of WSN coverage optimization experiments with different parameters are carried out. The first group of experiments proved that our algorithm improved coverage ratio and convergence compared with the former algorithms. The second and third groups of experiments compared Yin–YangPIO with some existing studies. The results show that Yin–YangPIO significantly enhance WSN coverage ratio.

In the future, the authors will improve the efficiency of the algorithm and apply the algorithm to WSN coverage optimization in more complex environments. In addition, the algorithm will be extended to more optimization problems in the IoT.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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