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Optimization of cluster resource indexing of Internet of Things based on improved ant colony algorithm

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Abstract
In Internet of Things, the resource distribution is random in space, which leads to the poor precision ratio of the cluster resource indexing of Internet of Things, so in order to improve the information fusion and dispatching ability of Internet of Things, it is necessary to optimize the resource indexing of Internet of Things. Therefore, an algorithm for cluster resource indexing of Internet of Things based on improved ant colony algorithm is proposed in this paper. Directed graph models are used to construct a distribution structure model of cluster resource indexing nodes of Internet of Things, carry out semantic association feature extraction in the cluster resource storage information flow of Internet of Things. And the improved ant colony algorithm is used to crawl and capture cluster information in Internet of Things. According to the ant colony trajectory information, the velocity and position of the cluster resource indexing of Internet of Things are updated, and the balanced ant colony algorithm is used to carry out the global search and local search to resources and initialize the clustering center, and the target function of the cluster resource indexing of Internet of Things is constructed and the optimization parameter is solved with the constraint condition of the minimum variance of the whole fitness. The strong ability of global optimization of the ant colony algorithm is used to realize resource indexing optimization. Simulation results show that the improved algorithm can quickly realize resource index convergence, effectively escape local minimum points, and has strong global search ability and relatively high resource indexing precision ratio.

Keywords Ant colony algorithm · Internet of things · Cluster resource · Indexing · Clustering

1 Introduction

With the development of Internet of Things technology, Internet of Things received considerable attention in resource scheduling and transmission with good real-time and strong object-oriented ability [1–3]. There is massive cluster resources in Internet of Things platform, so it is required to optimize the scheduling and retrieval of massive cluster resources, and improve classification management and information processing capacity of resources [4–6]. The client of cluster resources in Internet of Things is done with multi-host and multi-database distribution to meet the demands of distributed storage and retrieval of cluster resources in Internet of Things. With the expansion of resource scale, the difficulty of indexing cluster resources in Internet of Things is larger. It is of great significance to study a more effective cluster resource indexing method for Internet of Things in improving resource scheduling and data transmission and reception of Internet of Things, so relative researches on resource indexing methods have received a great attention [7–9].

At present, the research on the development of cluster resource indexing of Internet of Things is based on database retrieval and optimal design of routing mechanism of Internet of Things. Data source, business logic, user interface and communication protocols are bundled together with the distribution model of link routing constructing Internet of Things in cellular, self-organizing and mixed way to achieve optimal retrieval of cluster resources [10–12]. Common cluster resource index methods include feature labeling method of spatial information points, fuzzy retrieval method, data clustering method and particle swarm optimiza-

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tion index method [13–15]. Some research achievement has been achieved in self-adaptive scheduling and classification indexing for cluster resource with web crawler and data clustering. In this paper, a method of indexing cluster resources of Internet of Things based on multi-layer fuzzy subtraction clustering algorithm is proposed in literature [16]. Combined with the improved particle swarm optimization, this proposed method can prevent the interference of neighboring data points and improves the security of Internet of Things information management platform in cluster resource indexing of Internet of Things, but the method is not high in the precision of large-scale resource indexing; In literature [17], a method of indexing cluster resources of Internet of Things based on association semantic fusion clustering is proposed, and association semantic fusion clustering is done with segmented fusion fuzzy clustering method to construct index target values and calculate the global optimal solution. And then the cluster resources of Internet of Things are optimized and indexed. The method has strong anti-interference ability in resource indexing, and its convergence is well during indexing, but this method will bring a great computational cost and its real-time performance of cluster resource indexing is poor.

Therefore, an algorithm of cluster resource indexing of Internet of Things based on improved ant colony algorithm is proposed in this paper. Firstly, directed graph models are used to construct a distribution structure model of cluster resource indexing nodes of Internet of Things, carry out semantic association feature extraction in the cluster resource storage information flow of Internet of Things. And the improved ant colony algorithm is used to crawl and capture cluster information in Internet of Things. According to the ant colony trajectory information, the velocity and position of the cluster resource indexing of Internet of Things are updated, and the balanced ant colony algorithm is used to carry out global search and local search to resources. The target function of the cluster resource indexing of Internet of Things is constructed and the optimization parameter is solved. The strong ability of global optimization of the ant colony algorithm is used to realize resource indexing optimization. Finally, the simulation experiment is carried out, which shows the superiority of this method in improving the performance of cluster resource indexing of Internet of Things.

Overall structure of the paper:

Part 1: Analysis the storage structure and data characteristics of cluster resources of internet of things.
Part 2: Directed graph models are used to construct a distribution structure model of cluster resource indexing nodes of Internet of Things, carry out semantic association feature extraction in the cluster resource storage information flow of Internet of Things. And the improved ant colony algorithm is used to crawl and capture cluster information in Internet of Things, we solve the cluster resource optimum indexing of Internet of Things.
Part 3: In order to test the application performance of this method in the realization of the cluster resource index of Internet of Things, a simulation experiment is carried out. Simulation results show that the improved algorithm has strong global search ability and relatively high resource indexing precision ratio.

2 Analysis of storage structure and data characteristics of cluster resources of internet of things

2.1 Principle analysis and resource storage distribution structure

In order to realize the cluster resource optimum indexing of Internet of Things, storage structure is analyzed with a directed graph analysis model, and a data structure model of resource distribution of Internet of Things is constructed, and the semantic feature extraction and the improved ant colony optimization algorithm are used to optimize cluster resource indexing [18]. According to the above design principle, the overall realization flow of cluster resource indexing of Internet of Things based on the improved ant colony algorithm is obtained as Fig. 1.

According to the overall realization process of the cluster resource indexing of Internet of Things network shown in Fig. 1, the cluster resource indexing algorithm is designed. Assuming that G_2 represents the intersection of the demantic feature distribution directed graph G_1 and G_2 of cluster resources of Internet of Things, in the semantic nodes of the directed graph G_1 and G_2, there are common nodes among neighborhood space A, B and C of cluster resources of Internet of Things, and neighborhood space A, B and C belong to G_1 and G_2 meantime. The distribution structure model of cluster resource indexing nodes of Internet of Things is constructed with directed graph models as shown in Fig. 2 According to the correlation characteristics between the nodes of resource distribution, the computation equation for the similarity degree of the node distribution of cluster resources of Internet of Things S_C is obtained as follows:

$$S_C = \frac{2n\left(D_1 \cap D_2\right)}{n\left(D_1\right) + n\left(D_2\right)} \tag{1}$$

where, $n\left(D_1\right)$ and $n\left(D_2\right)$ represent the number of indexing nodes in directed graph G_1 and G_2 of cluster resources of Internet of Things respectively; $n\left(D_1 \cap D_2\right)$ represents the number of common nodes. The analysis of Fig. 2 shows that connectivity of cluster resource index channel of Internet of Things in G_1 and G_2 are:

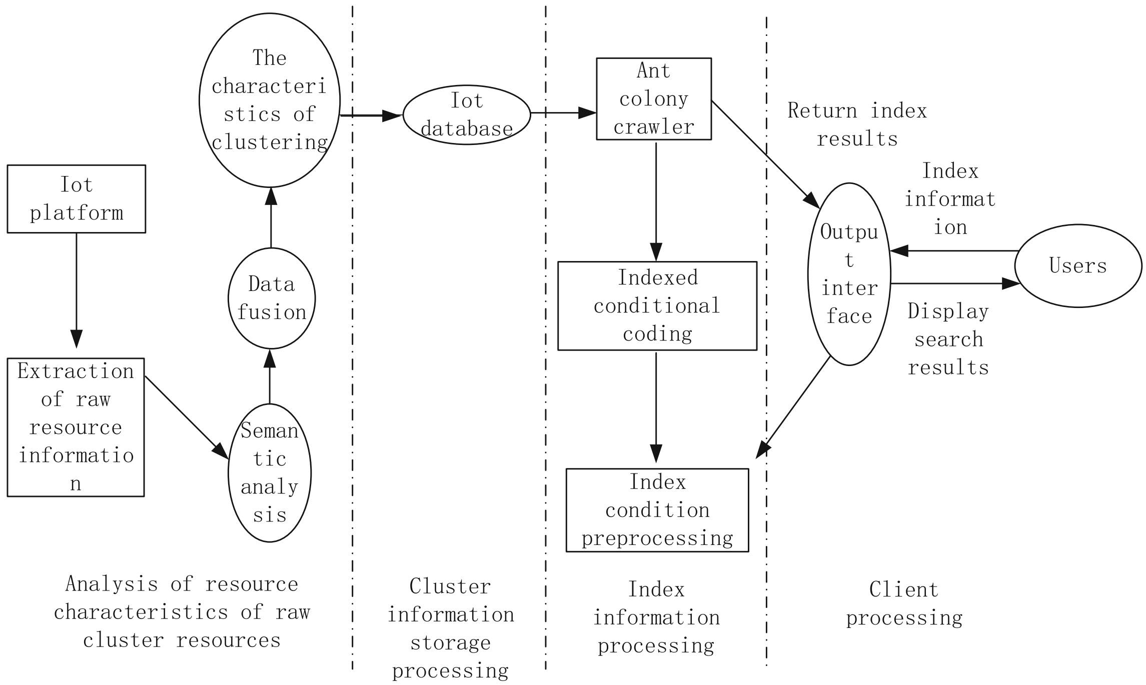


Fig. 1 Overall realization flow of cluster resource indexing of Internet of Things

$$a = \frac{2n\left(G_C\right)}{2n\left(G_C\right) + m_{G_C}\left(G_1\right) + m_{G_C}\left(G_2\right)} \tag{2}$$

where, $n\left(G_C\right)$ represents the number of columns in the resource indexing stack in G_2; $m_{G_C}\left(G_1\right) + m_{G_C}\left(G_2\right)$ represents the number of arcs related to G_2 in G_1 and G_2.

2.2 Analysis of data characteristics of cluster resource of Internet of Things

Assuming that the binary sequence of random information source of cluster resources of Internet of Things X is represented by $a_0, a_1, a_2, \ldots$, and it is inspected with the number of data in internal boundary unit, a set of prime numbers $\left\{p_{i,j}\right\}_{1 \le i,j \le \mu}$ is generated, where the size of $p_{i,j}$ is η bits. $\{a_i\}$ is used to represent the dense cluster of different shapes. Assuming that $H_1 : \{0,1\}^* \to Z_q^*$ and $H_0 : \{0,1\}^* \to Z_q^*$, n represents the number of elements in the data set of cluster resource data of Internet of Things r. Select a cluster internal data with sorting column $i(i \le n)$ in dense cluster r, give value X to the data, and calculate the geometrical distance between the spatial distribution grid and the initial cell. When $R = g^{r_1}$ is met, the code of cluster resource indexing is output:

$$h_1 = H_1\{ID_b, w_b\} \tag{3}$$

$$h = H_2\{m, R, ID_a, u_a, r_2\} \tag{4}$$

Assuming that $\{\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_m\}$ is the basis vector of high frequency data of the cluster resource in Internet of Things, the sparse distribution of this set of base vector is defined as follows:

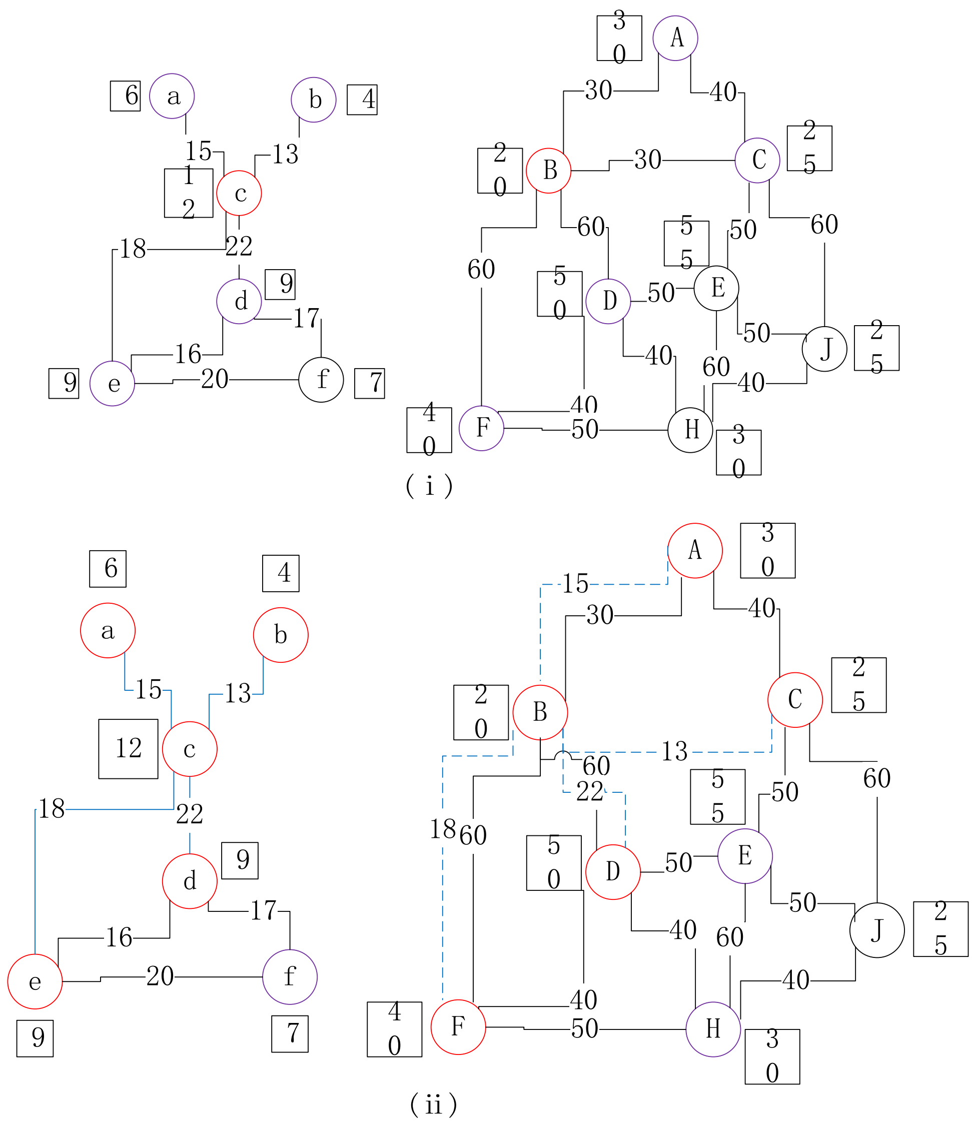
$$\mathrm{span}(\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_m) = \{[\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_m]\boldsymbol{x} : \boldsymbol{x} \in R^n\} \tag{5}$$

According to the above definition as well as structure characteristics of each cluster itself of transport channel of Internet of Things, for any set of vectors $\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_m$, the relative gird density of information stenographic object p meets $dist\left(p, o'\right) \le dist\left(p, o\right)$, and d orthogonal vectors $\boldsymbol{v}_1^*, \boldsymbol{v}_2^*, \ldots, \boldsymbol{v}_m^*$ in one-dimensional space satisfies:

$$\begin{aligned} \boldsymbol{v}_i^* &= \boldsymbol{v}_i - \sum_{j=1}^{i-1} \mu_{i,j} \boldsymbol{v}_j^* \\ \boldsymbol{v}_1^* &= \boldsymbol{v}_1 \end{aligned} \tag{6}$$

where, $i = 1, \ldots, m$. The write position of the cluster resource information indexing algorithm is obtained, and it is $\mu_{i,j} = \frac{\left\langle \boldsymbol{v}_i, \boldsymbol{v}_j^* \right\rangle}{\left\langle \boldsymbol{v}_j^*, \boldsymbol{v}_j^* \right\rangle}$. In a data transmission cycle, select a integer $\Pi_{i,b} = \chi_{i,b}^{\Pi} - \delta_{i,b}^{\Pi}\ (1 \le i \le \mu)$ as discrete source, and record the probability of each cluster resource classification cluster r_i as $P(r_i)$, $P(r_i) \ge 0$ and $\sum_{i=1}^{n} P(r_i) = 0$. Combined with the characteristics of cluster resource indexing, the semantic association feature extraction is carried out in the cluster

Fig. 2 Distribution structure model of cluster resource indexing nodes of Internet of Things



resource storage information flow of Internet of Things, and the improved ant colony algorithm is used to crawl and capture the information.

3 Resource indexing algorithm

3.1 Cluster information capture of Internet of Things with crawler

Based resource storage information flow on the idea that directed graph models are used to construct a distribution structure model of cluster resource indexing nodes of Internet of Things and carry out semantic association feature extraction in the of Internet of Things, the optimal design of the cluster resource indexing of Internet of Things is done, and an algorithm for cluster resource indexing of Internet of Things based on improved ant colony algorithm is proposed in this paper. The improved ant colony algorithm is used to crawl and capture cluster information in Internet of Things. Assuming that the optimal mobility probability in the cluster resource search process is $P_{ij}^{best}(k)$, and the length of the ant search is S, according to the ant information concentration, the position of ant colony i in the moment $k+1$ can be calculated as follows:

$$x_i(k+1) = x_i(k) + s\left(\frac{x_j(k) - x_i(k)}{\left\|x_j(k) - x_i(k)\right\|}\right) \tag{7}$$

Based on the error backstepping transform, the error function for information search of the zero point trajectory of the ant colony depth is obtained as follows:

$$E = \sum_{j=1}^{q} E_j / \left(q^* k\right) \text{ where } \mathrm{E_j} = \sum_{\mathrm{k}} ''^2_{\mathrm{k}} = \sum_{\mathrm{k}} (\mathrm{d_k} - \mathrm{c_k})^2 \tag{8}$$

where, q is the number of samples of cluster resource input in Internet of Things; ε_k is focal sensitivity coefficient of information search; the sociohormone is searched in the D-dimensional space according to the tphase shifting velocity $V_i = (\upsilon_{i1}, \upsilon_{i2}, \ldots, \upsilon_{iD})^T$ and position $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})^T$ of ant colony. Use m ant colonies to consist an ant population, set the scale of the ant population as M, total iteration times of the algorithm as T. Then the distribution vector of searching location of the i-th ant colony is $V_i = \upsilon(\upsilon\upsilon_{i1}, \upsilon_{i2}, \ldots, \upsilon_{iD})$. In consideration of global optimization, the ant gcolony position update formula is obtained as follows with the adaptive error correction:

$$\begin{cases} v_{id}^{t+1} = \omega v_{id}^{t} + c_1 r_1 (p_{id} - x_{id}^{t}) + c_2 r_2 (p_{gd} - x_{id}^{t}) \\ x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \end{cases} \tag{9}$$

According to the trajectory information of an ant colony, the velocity and position of the cluster resource indexing of Internet of Things are updated. And the balanced ant colony algorithm is used for global searching and local searching for resources [19]. In the iterative search process, the global optimal ant subscript g_{best} is recorded, and the weight of each ant colony is calculated according to the velocity and speed of the ant in the cluster resource indexing space:

$$\tilde{w}_k^i = \tilde{w}_{k-1}^i \frac{p(z_k/\tilde{x}_k^i)\,p(\tilde{x}_k^i/x_{k-1}^i)}{q(\tilde{x}_k^i/x_{k-1}^i)} \tag{10}$$

For each generation of ant colony, set a threshold ξ and calculate the diversity factor of cluster resource distribution mf, and compare the factor with the upper and lower limits of inertia weight. If $mf < \xi$, change U, and adopt a new U, and judge whether the termination conditions are met. If the conditions are met, record the optimal global solution, change ant colony, obtain the initial membership matrix of the d-dimension ($1 \le d \le D$) ant colony based on a number of local minimum points, replace the i-th dimension of X_{best} position with the i-th dimension of the $X_{\text{ex}-\text{best}}$, adjust the inertia weight in a non-linear way, and obtain the optimal global ant colony potions at present with the following equation:

$$\begin{aligned} V_{id} &= wV_{id} + c_1 rand()(p_{id} - x_{id}) \\ &\quad + c_2 Rand()(p_{gd} - x_{id}) \end{aligned} \tag{11}$$

$$x_{id} = x_{id} + V_{id} \tag{12}$$

where, w is inertia weight; c_1 and c_2 are fitness value of each ant colony respectively. The information vector captured with cluster information crawler of Internet of Things is obtained with the improved ant colony algorithm as follows:

Position vector: $\mathbf{X}_i = \{x_{i,1}, x_{i,2}, x_{i,3} \ldots\ldots x_{i,D}\}$

Velocity vector: $\mathbf{V}_i = \{v_{i,1}, v_{i,2}, v_{i,3} \ldots\ldots v_{i,D}\}$

Optimal individual position vector; $\mathbf{p}_i = \{p_{i,1}, p_{i,2}, \ldots\ldots p_{i,D}\}$

3.2 Solving of cluster resource optimum indexing of Internet of Things

With the balanced ant colony algorithm, global research and local research are done and the clustering center is initialized. The update equation of ant colony algorithm is as follows:

$$ea = (W_\beta - W_\alpha)/sum(1 : Iterations) \tag{13}$$

$$\omega = \omega - (Iterations - iter) \times ea \tag{14}$$

where W_α and w_β represent the upper and lower limits of inertia weight respectively. Set the variable of the target function of cluster resource indexing as Q, and set X_i as the solution of variable Q in the space and take the minimum overall fitness variance as a constraint. Then a function corresponding to each X_i is:

$$l_i(k) = (1 - \rho) l_i(k-1) + \gamma f(x_i(k)) \tag{15}$$

where, f_i is the optimal global value of $X_{i;}\, P_{ij}(k)$ represents the probability that the i-th ant move to the j-th ant at time k when gathering to its neighbor. Ant colony updates its velocity and position based on individual optimum and global optimum, so the strong ability of global optimization of the ant colony algorithm can used to obtain the global optimal point before the stabilization phase $X_{\text{ex}-\text{best.}}$ During the iterative search process, the position of the i-th ant at time $k+1$ is:

$$x_i(k+1) = x_i(k) + s\left(\frac{x_j(k) - x_i(k)}{\left\|x_j(k) - x_i(k)\right\|}\right) \tag{16}$$

where, $\|\vec{x}\|$ represents the norm of $\vec{x}$. In consideration of Golan optimization min{f(x)},the posteriori probability of the cluster resource indexing of Internet of Things $p(x_0)$ is obtained. According to the inertia weight of the ant colony, the accurate probability of the cluster resource indexing is obtained:

$$P_{ij}(k) = \frac{(l_j(k) - l_i(k))\eta_{ij}(k)}{\sum\limits_{j \in N_i(k)} (l_j(k) - l_i(k))\eta_{ij}(k)} \tag{17}$$

In this case, the position of ant i for resource indexing in D-dimension space can be expressed as $X_i = (x_{i1}, x_{i2}, \ldots x_{iD})$. The probability that the i-th ant accurately index cluster resources according to the optimal individual position is recorded as $P_i = (p_{i1}, p_{i2}, \ldots p_{iD})$.

$$j \in N_i(k),\ N_i(k) = \{\left\|x_j(k) - x_i(k)\right\| < r_d(k)\} \tag{18}$$

where, $\eta_{ij}(k)$ is the ant colony trajectory information. The optimal moving probability is $P_{ij}^{best}(k)$. The moving step length under the control of the ant colony coefficient is S. And the optimal parameter is solved with adaptive algorithm according to the target function of cluster resource indexing of Internet of Things to realize cluster resource indexing of Internet of Things.

4 Simulation experiment and result analysis

In order to test the application performance of this method in the realization of the cluster resource index of Internet of Things, a simulation experiment is carried out. The environment of the experiment, CPU: Intel Core i3-370; master frequency: 2.93 GHz; memory: 2 GB; and Matlab7 software is used for algorithm design. Parameter setting: $Rn = 56$, $\varepsilon = 0.53$, $\mu_\lambda = 0.71$. The population size of the ant colony is set to 20, the number of iterations of the cluster resource search is 6000 times, the acceleration constant C1 = 2, C2 = 2, and the evaluation coefficient of resource index optimization is 0.21, the maximum number of updates for the indexing is 1.2×10^5. the independent search runs 30 times, and a better global optimal value is searched 4.24423319317e + 05. Rastrigrin function suitable for operation of a large number of cases, we can effective test the application performance of this method in the realization of the cluster resource index of Internet of Things by selecting the Rastrigrin function as test function. The Rastrigrin function:

$$f_1(x) = 10 \times n + \sum_{i=1}^{n} (x_i^2 - 10 \times \cos(2 \times \pi \times x_i)) \quad (19)$$

According to the above simulation environment and parameter setting, a simulation of cluster resource indexing of Internet of Things is done. The output results of cluster resource indexing of Internet of Things are obtained with the method of indexing cluster resources of Internet of Things based on multi-layer fuzzy subtraction clustering algorithm in literature [16], the method of indexing cluster resources of Internet of Things based on association semantic fusion clustering in literature [17], and this method as shown in Figs. 3, 4 and 5.

The analysis of Figs. 3, 4 and 5 shows that with the method of indexing cluster resources of Internet of Things based on multi-layer fuzzy subtraction clustering algorithm and the method of indexing cluster resources of Internet of Things based on association semantic fusion clustering, the cluster resources of Internet of Things are distributed in a messy, the clustering is poor, and it is difficult to accurately index target information. The use of this method for Internet of Things cluster resource indexing can accurately capture luster information of Internet of Things and the output index information clustering performance is good. In order to compare the performance of those algorithms, take f_1 as a test function to analyze the optimization and convergence performance of those algorithms. The results are obtained as shown in Figs. 6 and 7.

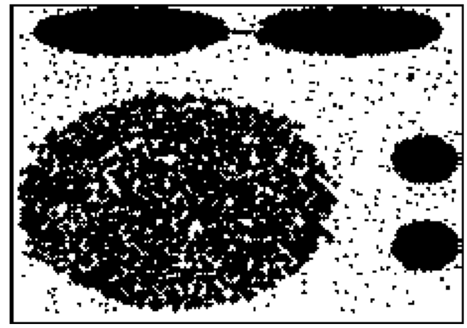


Fig. 3 Output result of cluster resource indexing of Internet of Things with the method in literature [16]

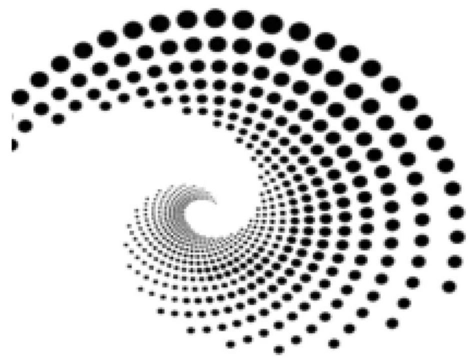


Fig. 4 Output result of cluster resource indexing of Internet of Things with the method in literature [17]

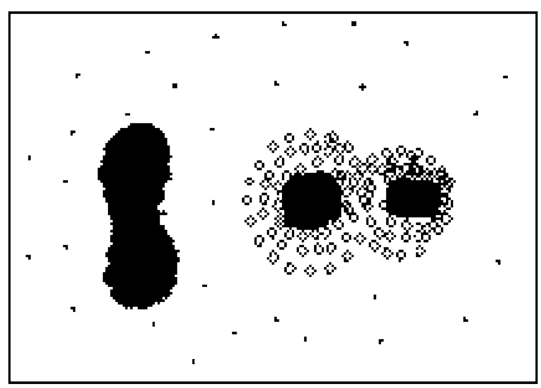


Fig. 5 Output result of cluster resource indexing of Internet of Things with the method proposed in this paper

Analysis of Figs. 6 and 7 shows that that this method has better optimization in cluster resource indexing of Internet of Things. Because traditional methods are more likely to fall into the local minimum points, and the improved algorithm can quickly achieve resource indexing convergence,

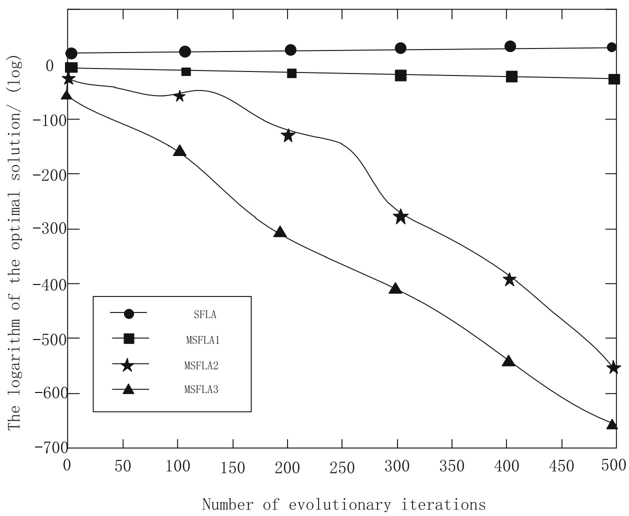


Fig. 6 Resource index optimization ability test

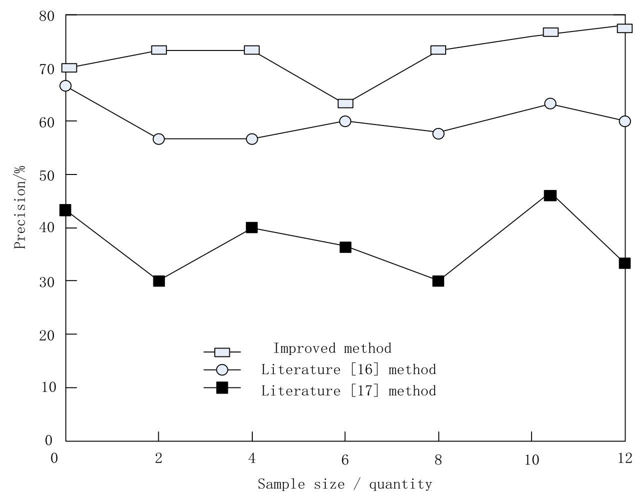


Fig. 8 Comparison of resource indexing precision ratio with different methods

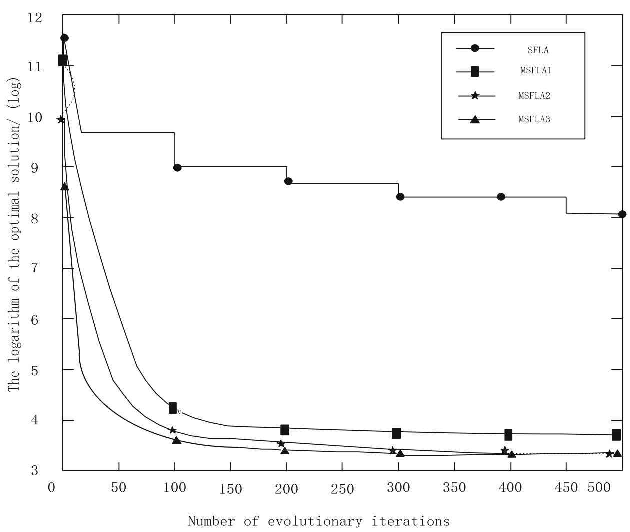


Fig. 7 Convergence test

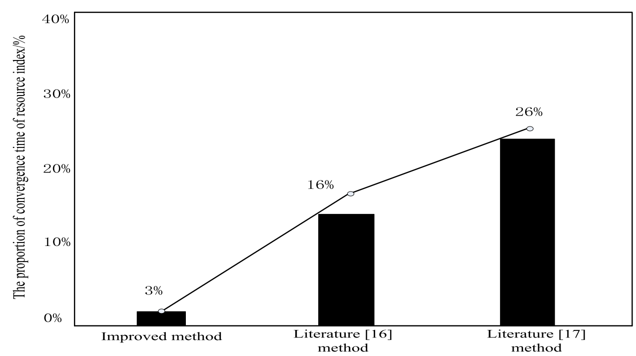


Fig. 9 Computational time cost of three method

and effectively escape local minimal points to improve the precision ratio of the cluster resource indexing.

In order to further verify the effectiveness and feasibility of the improved method in the cluster resource indexing of Internet of Things, the improved method is compared with the method of indexing cluster resources of Internet of Things based on multi-layer fuzzy subtraction clustering algorithm in literature [16] and the method of indexing cluster resources of Internet of Things based on association semantic fusion clustering in literature [17] to carry out simulation experiment comparison analysis to different cluster resources. The simulation results of different resource search methods are shown in Fig. 8.

Figure 8 shows that when the method of indexing cluster resources of Internet of Things based on multi-layer fuzzy subtraction clustering algorithm in literature [16] is used, the precision ratio is about 38.6%, and the there is a significant change and stability is poor; when the method of indexing cluster resources of Internet of Things based on association semantic fusion clustering in literature [17] is used, the precision ratios about 53.9%, and there is a stable phenomenon in a short term, but the precision ration tends to decline finally; when the improved algorithm is used, the precision ratio is about 72.8%, which is higher than that of methods in literature [16] and literature [17] by about 34.2, 18.9% respectively, so this method has certain advantages. The computational time cost of different resource search methods are shown in Fig. 9.

Figure 9 shows that the resource index convergence time of the improved method is much lower than that of the literature [16] and literature [17] method, traditional method bring a great computational cost and the real-time performance of cluster resource indexing is poor, but the improved algorithm can quickly realize resource index convergence.

5 Conclusion

In this paper, the cluster resource optimum indexing of Internet of Things is studied, and an algorithm for cluster resource indexing of Internet of Things based on improved ant colony algorithm is proposed. Directed graph models are used to construct a distribution structure model of cluster resource indexing nodes of Internet of Things, carry out semantic association feature extraction in the cluster resource storage information flow of Internet of Things. And the improved ant colony algorithm is used to crawl and capture cluster information in Internet of Things. According to the ant colony trajectory information, the velocity and position of the cluster resource indexing of Internet of Things are updated, and the balanced ant colony algorithm is used to carry out global search and local search to resources. The target function of the cluster resource indexing of Internet of Things is constructed and the optimization parameter is solved with the constraint condition of the minimum variance of the whole fitness. The strong ability of global optimization of the ant colony algorithm is used to realize resource optimum indexing. This method is strong in global optimization and good in convergence in cluster resource indexing of Internet of Things, which improves the indexing ability to target resources, and it has a good application value in the information platform construction and resource scheduling of Internet of Things.

Research work in the future

The research on network cluster resource index matter is still in the initial stage, the networking cluster resource itself contains more content, the influence factors are more complex, the existing literature research is not deep enough and the research content is relatively one-sided. Later researchers can comprehensively and deeply explore the cluster index of Internet of things. The author thinks that it can be studied from the following two aspects:

(1) Other algorithms can be used to optimize the cluster index of the Internet of things, and a more efficient and convenient calculation method will be selected;
(2) How does the semantic association feature extraction method in the cluster resource storage information flow of the Internet of things and how does it work on the cluster resource index?

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