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Research on Wireless Sensor Network Coverage Based on Improved Particle Swarm Optimization Algorithm

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***Abstract*—In order to improve the network coverage, this paper presents the research on wireless sensor network coverage based on improved particle swarm optimization algorithmfor wireless sensor nodes that are randomly deployed in a certain area.In this paper, we use the regional network coverage as the target objective function, and combine various improved particle swarm optimization algorithms to optimize the deployment location of all nodes to enhance the area coverage. The experimental results show that the influence levelof different perceived radius on the optimization performance of the network coverage is different. At the same time, the optimization performance comparison graph of improving the network coverage by using the standard particle swarm optimization algorithm, the chaos particle swarm optimization algorithm and the breeding particle swarm optimization algorithm is given, and it is proved that the latter twoalgorithms solve the wireless sensornetwork coverage better than the firstalgorithm.**

Keywords-Wirelesssensor;Node;Network coverage; Particle swarm optimization;Perceivedradius

I. INTRODUCTION

Wireless Sensor Networks (WSN) consists of a number of inexpensive, low-energy sensor nodes, as a platform for physical world and human information exchange [1-2].Due to the limited computing power, sensing range and transmission range of each sensor, the wireless sensor network transmits the collected data to the cluster head sensor by multi-hop to monitor whether there is an anomaly in the area [3].The deployment of sensor nodes is very important, it affects the network coverage, communication costs and management resources, so WSN node deployment strategy is an urgent problem [4].

Particle swarm optimization (PSO) algorithm is widely used in multi-dimensional function optimization problem. It has the characteristics of simple structure, easy implementation, no gradient information and few parameters. It has become a hot research algorithm in the field of intelligent optimization at home and abroad [5-7].LinZhu-liangpresented particle fire optimization based on forest fire detection system of wireless sensor network [8] improved the network performance. However, the PSO algorithm is prematurely convergent and easy to fall into the local optimal value.Therefore, the improved particle swarm algorithm is continually proposed by researchers:According to the PSO algorithmdoes not have traversal type, the chaotic map is added to the standard particle swarm optimization algorithm. When the algorithm is premature, the chaotic search of the population makes it possible to jump out of the local optimal [9]; Chaos Particle Swarm Optimization (CPSO) algorithm improves the accuracy and efficiency of solving.Liu Wei-tingproposed a wireless sensor network coverage optimization based on the CPSO algorithm [10].Although the PSO algorithm has overcome the shortcomings of the local optimum, the ability of the algorithm to keep the population diversity is relatively general and the convergence speed is not improved obviously.According to the shortcomings of early convergence and late iterations of PSO algorithm, Li Ji proposed the Breeding Particle Swarm Optimization (BPSO) algorithm, and introduced the genetic algorithm (GA) into the PSO algorithm to increase the diversity of the particles, using the adaptive inertia weight to improve the convergence rate of the algorithm [11].Wang Jun proposed a three-dimensional cross-particle swarm optimization algorithm for wireless sensor networks [12]. Although the population diversity is better maintained, the ability to jump into local optimum is general.

Based on the above analysis, this paper respectivelystudies the coverage of wireless sensor networks based on PSO, CPSO and BPSO, and embodies the advantages and disadvantages of the algorithm.A wireless sensor coverage based on improved particle swarm optimizationis proposed for wireless sensor nodes that are randomly deployed in a certain area.The network coverage is used as the objective function, combined with the particle swarm optimization algorithm, and the deployment location of all nodes is optimized to enhance the area coverage.The experimental results show that the influence level of different perceived radius on the optimization performance of the network coverage and the optimization performance comparison graph of improving the network coverage by usingthe standard particle swarm optimization algorithm, the chaos particle swarm optimization algorithm and the breeding particle swarm optimization algorithm, and prove that the latter two algorithms solve the network coverage better than the first algorithm.

II. WIRELESS SENSOR NETWORK COVERAGE MODEL

A. Node and Node Set Coverage

Suppose there is a monitoring area for the two-dimensional plane A .In the region A , thesensor nodes with the same parameters are placed, and the coordinates of each node are (x_i, y_i) , where $i = 1, 2, \cdots, N$ .So that the sensor radius of each sensor node r , communication radius R .In this paper, in order to ensure the connectivity of the wireless sensor network, considering the wireless interference and other factors, the communication radius is set to twice the perceived radius, which is $R = 2r$ .The sensor node set is denoted by $C = \{c_1, c_2, \cdots, c_N\}$, where the monitoring field of the i sensor node is centered on the position coordinate (x_i, y_i) and r is the circle of the monitoring radius, denoted by $c_i = \{x_i, y_i, r\}$.

Assuming that a detection area A is digitally discredited into $m \times n$ pixels whose coordinate are denoted by $(x_j, y_j), j = 1, 2, \cdots, m \times n$ .The distance between the j pixel and the i sensor node is $d(c_i, p_j) = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$ .Assuming that the event at which the j pixel is covered by the i sensor node is r_{ij} , the probability of occurrence of event r_{ij} is $P\{r_{ij}\}$, then the probability [8] that the pixel (x_j, y_j) is covered by the sensor node c_i is:

$$P_{\text{cov}}(x_j, y_j, ci) = \begin{cases} 1, & if\ d(c_i, p_j) < r \\ 0, & otherwise \end{cases} \tag{1}$$

However, in the practical application, the interference of the monitoring environment, noise and other factors makes the sensor nodes with a certain probability distribution, according to reference [13] we can see the node monitoring probability distribution is as follows:

$$\begin{aligned} & P_{\text{cov}}(x_j, y_j, ci) \\ & = \begin{cases} 1, & if\ d(c_i, p_j) \le r - re \\ e^{(-\alpha_1 \lambda_1^{\beta_1})/\lambda_2^{\beta_2} + \alpha_2}, & if\ r - r_e < d(c_i, p_j) < r + r_e \\ 0, & otherwise \end{cases} \end{aligned} \tag{2}$$

In equation (2), r_e $(0 < r_e < r)$ is the measurement uncertainty parameter of the sensor node, $\alpha_1, \alpha_2, \beta_1, \beta_2 > 0$ is the measurement parameter about the characteristics of the sensor node, where $\lambda_1 = r_e - r + d(c_i, p_j), \lambda_2 = r_e + r - d(c_i, p_j)$ .The model reflects the characteristics of infrared and ultrasonic sensor isometric devices.Considering that the target pixel j is simultaneously covered by multiple sensor nodes, the joint monitoring probability [14] is:

$$\begin{aligned} & P_{\text{cov}}(Cov_j) = 1 - \prod_{c_i \in Cov_j} (1 - P_{\text{cov}}(x_j, y_j, c_i)) \\ & i = 1, 2, \cdots N;\ j = 1, 2, \cdots, m \times n \end{aligned} \tag{3}$$

Where Cov_j is the set of sensor nodes that measure the target pixel point j .

B. Monitor Area Coverage

From the above assumptions, the region A has $m \times n$ pixels. In this paper, we use the joint monitoring probability of the node set to measure whether each target pixel is covered, so that P_{th} is the expected coverage threshold, then

$$P_{\text{cov}}(Cov_j) = \begin{cases} 0, & if \quad P_{\text{cov}}(Cov_j) < p_{th} \\ 1, & if \quad P_{\text{cov}}(Cov_j) \ge p_{th} \end{cases} \tag{4}$$

Where $P_{\text{cov}}(Cov_j) = 1$ indicates that the target pixel j is overwritten; otherwise, the target pixel j is not overwritten.This paper establishes a grid intersection that represents the coverage of the sensor, where the grid intersection is also called the sampling point [14].The effective coverage points $(N_{effective})$ are calculated by the formula (2-4), and the number of sampling points of the whole sensor field is $m \times n$, so the coverage rate ϕ_p of the monitoring area A can be calculated as follows:

$$\phi_p = \frac{N_{effective}}{m \times n} = \frac{\sum_j P_{\text{cov}}(Cov_j)}{m \times n} \tag{5}$$

C. Optimization Model of Wireless Sensor NetworkCoverage

According to the above analysis, this paper takes the monitoring area coverage as the objective function, the node in the monitoring area as the constraint condition, and establishes the wireless sensor network coverage optimization model according to the formula (2-5):

$$\begin{aligned} & \text{Maxmize} \quad \phi_p = \frac{N_{effective}}{m \times n} = \frac{\sum_j P_{\text{cov}}(Cov_j)}{m \times n} \\ & s.t. \qquad \begin{cases} 0 \le x_i \le m \\ 0 \le y_i \le n \end{cases} \end{aligned} \tag{6}$$

III. NETWORK COVERAGE OPTIMIZATION BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION

A. Standard Particle Swarm Algorithm Principle

A group of M particles in the D dimension search space at a certain speed flight, PSO algorithm initialize a group of random particles, through the iterative to find the optimal solution. Where the speed of each generation of particles, the location update formula [5-6] as follows:

$$\begin{aligned} v_{ij}(n+1) &= W * v_{ij}(n) + c1 * rand * (pbest_{ij} - x_{ij}) + \\ & c2 * rand * (gbest - x_{ij}) \\ & i = 1,2,\ldots M;\ j = 1,2,\ldots D \end{aligned} \tag{7}$$

$$\begin{aligned} & x_{ij}(n+1) = x_{ij}(n) + v_{ij}(n+1), \\ & i = 1,2,\ldots M;\ j = 1,2,\ldots D \end{aligned} \tag{8}$$

Where v_i is the velocity vector of the i particle; x_i is the current position of the i particle; $pbest_i$ is the position of the optimal solution found by the i particle; $gbest$ is the position of the optimal solution currently found by the whole population; $c1, c2$ is the learning factor to respectivelyadjust the particle attractionstrength; $rand$ is the random number between $(0,1)$; W is the inertia coefficient, which is calculated as follows:

$$W(t) = 0.9 - \frac{t}{\max number} \times 0.5 \tag{9}$$

B. Coverage Optimization Design Based on PSOAlgorithm

Assuming that the monitoring area A is divided into several pixels with an area of 1, N sensor nodes are randomly deployed in the monitoring area. The coverage optimization based on the PSO algorithm is as follows:

Step1: Calculate the coverage of each pixel node for each sensor node according to (2);

Step2: Calculate the joint coverage of each pixel node for each sensor node according to (3);

Step3: According to (4-5) to calculate the coverage of the region, it istheobjective function, in the particle swarm algorithm also known as fitness.

Assuming that there are M particles, since the N sensors are deployed in the two-dimensional space, each particle has $D = 2 \times N$ -dimensional solution space that is $x = (x_1, x_2, \ldots x_D)$. The PSO algorithm is as follows:

Step1: Randomly generate the position and velocity of each particle in the monitoring area;

Step2:Update the position and velocity of each particle according to (7-9);

Step3: Calculate the fitness of each particle according to the optimization objective function;

Step4:Compare the particle fitness and the fitness ofits own best position, if better, and then set the new $pbest$;

Step5:Compare the fitness of each particle and the fitness of the best position in the population, if better, set the new $gbest$;

Step6:Until the maximum number of iterations is reached, the algorithm stops, otherwise proceed to step 2;

Step7: Output the optimal fitness and the corresponding particle position.

C. Chaotic Particle Swarm Algorithm

The main idea of the chaotic particle swarm algorithm is to generate a large number of initial groups by using the traversal type of chaotic motion, and select the optimal initial population to generate chaotic perturbations to the current particle individuals, so that the local extreme value interval can be jumped out. The random motion state usually obtained from the deterministic equation is called chaos. In this paper, Logistic map is used, which is a typical chaotic system. The iterative formula is:

$$z_{D+1} = \mu z_D (1 - z_D), D = 0,1,2,\ldots \tag{10}$$

The Logistic system is completely in the chaotic state when the control parameter $\mu = 4$ and $0 \le z_0 \le 1$ .The mapping of the chaotic to the optimization variables is:

$$\begin{aligned} & x_{ij} = xmin_j + z_D \times (xmax_j - xmin_j), \\ & i = 1,2,\ldots M,\ j = 1,2,\ldots D \end{aligned} \tag{11}$$

Where $xmin \le x \le xmax$ and $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$. According to the idea of chaos search, a small amount of chaotic perturbation is added to the current optimal solution, which is

$$z' = (1-\gamma)\psi^* + \gamma z \tag{12}$$

Where $\psi^* = \dfrac{x^* - xmin}{xmax - xmin}$ is the optimal chaotic vector formed by the current optimal solution x^* mapping, γ is the adjustment parameter of $[0,1]$, and z' is the vector obtained by adding a small amount of chaotic perturbationat the present optimal solution x^* [15-17].

D. Coverage Optimization Design Based on CPSO Algorithm

Step1:Randomly generate a D-dimensionalvector $z_1 = (z_{11}, z_{12}, \ldots, z_{1D})$ between $[0,1]$; generate M vectors $z_1, z_2, \ldots, z_M$ according to (10). According to (11), their components are carrier to the range of the optimal variables. Calculate the fitness of the initial particle swarm, and chose the better M_0 solutions as the initial solutions and randomly generate M_0 initial velocities.

Step2: Compare the particle fitness and the fitness ofits own best position, if better, and then set the new $pbest$;

Step3: Compare the fitness of each particle and the fitness of the best position in the population, if better, set the new $gbest$;

Step4: Update the position and velocity of each particle according to (7-9);

Syep5:The population optimal position $gbest$ is updated by a small amount of chaotic perturbations. If the number of current iterations is greater than or equal to $2/3$ times the total number of iterations, which is $MaxC \geq (2/3)MaxDT$ .A small amount of chaotic perturbation is added to the optimal position of the population according to (12), and the new chaotic variable is carried to the optimization variable according to (11).

Step6: Until the maximum number of iterations is reached, the algorithm stops, otherwise proceed to step 4;

Step7: Output the optimal fitness and the corresponding particle position.

E. The Principle of Cross Particle Swarm Algorithm

The main idea of the breeding particle swarm optimization algorithm: in the iterative process, the first half of the particles with good fitness directly into the next generation, and the latter half of the particles will be two pairs of pairs, and use the same crossover operation with the genetic algorithm to generate the same number of offspring with the parent number, and then compared with the parent, the better half of the fine particles into the next generation. This ensures that the number of particles remain unchanged.The breeding operation not only enhances the diversity of particles but also avoids the local optimum value, which helps to speed up the iterative convergence [18].

According to the breeding operation of the genetic algorithm, the position and velocity formula of the offspring particles are as follows:

$$\begin{aligned} child_1(x) &= pb \times parent_1(x) + (1-pb) \times parent_2(x) \\ child_2(x) &= pb \times parent_2(x) + (1-pb) \times parent_1(x) \end{aligned} \tag{13}$$

$$\begin{aligned} child_1(v) &= \frac{parent_1(v) + parent_2(v)}{\left|parent_1(v) + parent_2(v)\right|} \times parent_1(v) \\ child_2(v) &= \frac{parent_1(v) + parent_2(v)}{\left|parent_1(v) + parent_2(v)\right|} \times parent_2(v) \end{aligned} \tag{14}$$

Where $child(x), parent(x)$ represents the position of the offspring particles and the parent particles, $child(v), parent(v)$ respectively represents the velocity of the offspring particles and the parent particles, x is the position of the particle of the optimized variable, v is the velocity of the particle, pb is the D-dimensional vector of the value between $[0,1]$ [11].

F. Coverage Optimization Design Based on BPSO Algorithm

Step1: Population initialization. Randomly generated the location of each particle, speedin the monitoring area;

Step2: Calculate the fitness of each particle according to the optimization objective function;

Step3: Compare the particle fitness and the fitness ofits own best position, if better, and then set the new $pbest$;

Step4: Compare the fitness of each particle and the fitness of the best position in the population, if better, set the new $gbest$;

Step5: Update the position and velocity of each particle according to (7-9);

Step6: Calculate the fitness of the updated particles, and sort them from large to small;

Step7: The first half of the particles with good fitness directly into the next generation, the latter half of the two pairs of particles to match, anduse the same genetic algorithm with the cross operation, according to (13-14) to generate the same number of parents with the child Generation, and then compared with the father, the better the first half of the fine particles into the next generation;

Step8: Data merges to form new offspring particles and updates individual extremes and global extremes;

Step9: Until the maximum number of iterations is reached, the algorithm stops, otherwise proceed to step 2.

IV. Simulations

A. Experimental Environment and Parameter Setting

By using a computer with a frequency of 2.30GHZ, the wireless sensor network coverage optimization simulation is carried out in MATLAB2014a environment.In this paper, we assume that the region is a square with a length of 20meters and a total of 20 sensor nodes with the same performance and the same size. The perceived radius of the sensor r be 3 meters, the communication radius R be $2 \times r = 6$ meters. Sensor node measurement uncertainty parameter $r_e = 0.4 \times r = 1.2$, $\alpha_1 = 1, \alpha_2 = 0, \beta_1 = 1, \beta_2 = 1.5$. In the particle swarm optimization algorithm, let the learning factor $c_i, i = 1,2$ be 2 and the maximum number of iterations $MaxDT$ be 1000 .The 20 wireless sensor nodes are randomly distributed in the area as shown in Fig.1, where $*$ is the node position, and the circle represents the perceived range of the node, and the corresponding network coverage is 53.75% .

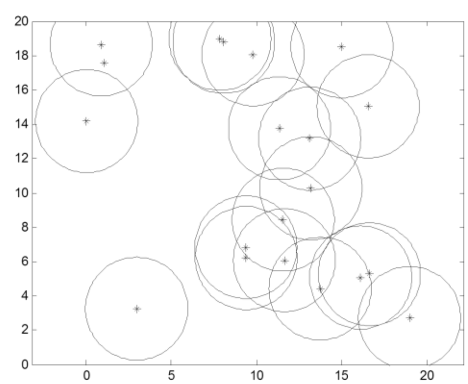

Figure 1. Monitoring area random distribution graph

B. Influence of Perceptual Radius on Network Coverage Optimization Performance

Under the same parameters and experimental environment, letthe number of particles M be 40 and the dimension D be $20\times 2 = 40$. By setting different perceive radius, the influence degree of different perceived radius on the network coverage optimization performance is analyzed.At the value of the node sensing radius r be $2, 2.5, 3, 3.5, 4, 5$ meters, the PSO algorithm optimizes the network coverage of the monitoring area as shown in Fig .2. The number of iterations and the optimal coverage of the corresponding algorithmare as shown in Table I.The following data conclude that the higher the sensor node perceived radius, the higher the wireless sensor network coverage optimization performance.When perceivedradius r be 3.5 meters, the network coverage has reached more than 90% , the monitoring area is almost all covered, and achieve the desired coverage effect. At the beginning of the network coverage growth rate is faster, with the increasing in perceived radius, network coverage growth rate has slowed, the number of iterations less and less.

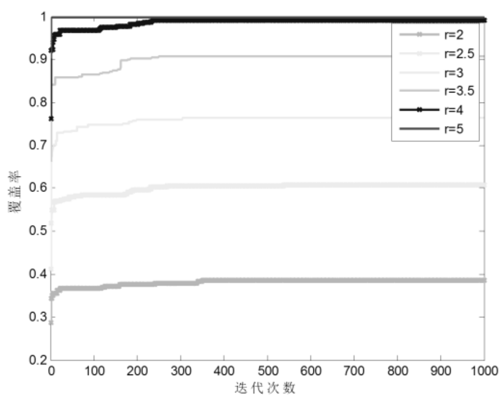

Figure 2. Theiteration graph of the different radius

TABLE I. THE NETWORK COVERAGE OPTIMIZATION PERFORMANCE OF DIFFERENT SENSING RADIUS

Area A network coverage optimization performance test						
Node perceived radius(m)	2	2.5	3	3.5	4	5
Number of iterations	351	539	305	249	236	4
Optimal coverage(%)	38.5	60.75	76.5	90.75	99.25	100

C. Performance Comparison of Network Coverage Based on PSO / CPSO / BPSO Algorithm

Under the same parameters and experimental environment, using respectively the standard particle swarm, chaos particle swarm and breeding particle swarm optimization algorithm to optimizethe regional network coverage. And the resulting node deployment situation isshown in Fig .3, Fig.4, and Fig .5. The corresponding optimal network coverage is $77.75\%, 78\%, 80\%$, and optimization performance comparison results shown in Fig. 6.

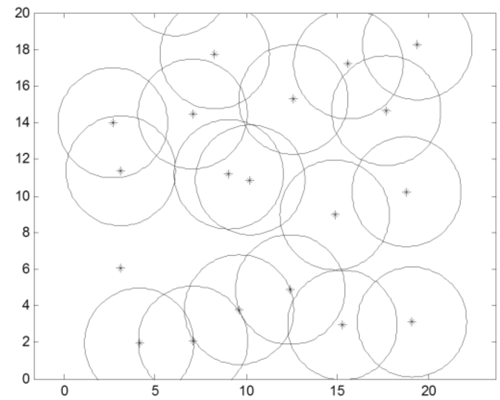

Figure 3. Optimized deployment graph for wireless sensor nodes based on standard particle swarm optimization

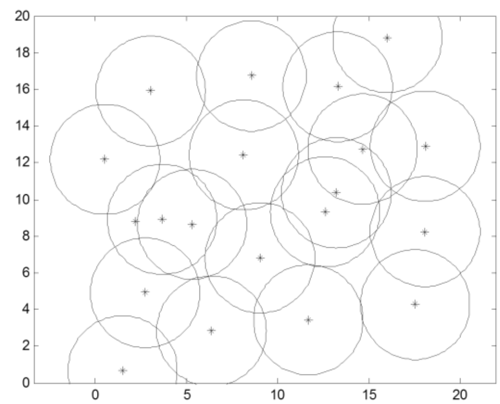

Figure 4. Optimized deployment graph for wireless sensor nodes based on chaos particle swarm optimization

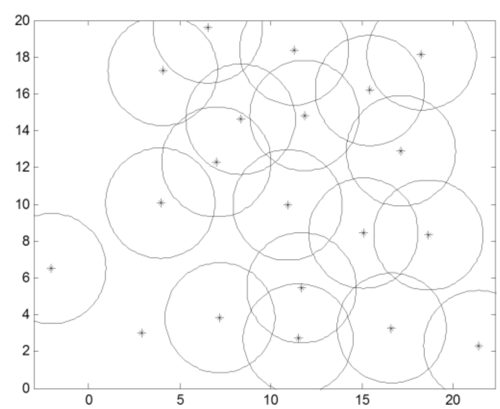

Figure 5. Optimized deployment graph for wireless sensor nodes based on breeding particle swarm optimization

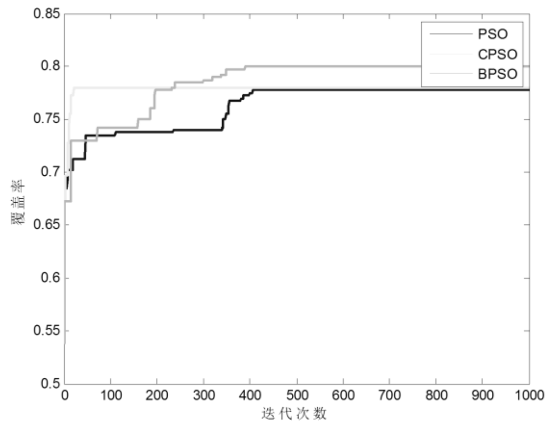

Figure 6. The comparison graph of the coverage performance of wireless sensor networks based on PSO / CPSO / BPSO algorithm

It can be seen from Fig.6 that the PSO algorithm has the lowest optimization result and the BPSO algorithm has the highest optimization result. The CPSO algorithm has the most number of iterations and the BPSO algorithm has the least number of iterations.It is shown that the PSO algorithm is easy to be trapped in the local optimum;the convergence degree of the late evolution is low; the ability that CPSO algorithm avoids falling into the local optimal is strong; the BPSO algorithm strongly maintains the population diversity and improves the convergence rate to a large extent.

V. CONCLUSIONSS

In this paper, we improve the coverage of wireless sensor networks by improving particle swarm optimization. Firstly, the mathematical model of wireless sensor network node, node set and region coverage is established, and the regional coverage formula is the optimization objective function.Then, the area coverage is taken as the fitness function, and the optimal deployment strategy and optimal coverage are solved in the particle swarm optimization algorithm.Finally, the simulation data show that the larger the node perceived radius, the better the network coverage optimization performance.By comparing the optimal performance of the three algorithms, such as standard particle swarm, chaotic particle swarm and cross particle swarm,it is proved that the latter two algorithms solve the network coverage better than the first algorithm.

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