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An Improved PSO Algorithm Based on Mutation Operator and Simulated Annealing

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Abstract

Particle swarm optimization (PSO) algorithm is simple stochastic global optimization technique, but it exists unbalanced global and local search ability, slow convergence speed and solving accuracy. An improved simulated annealing (ISAM) algorithm is introduced into the PSO algorithm with crossover and Gauss mutation to propose an improved PSO (ISAMPSO) algorithm based on the mutation operator and simulated annealing in this paper. In the ISAMPSO algorithm, the mutation operator of genetic algorithm is introduced into the SA algorithm as a generation mechanism of new solution in order to propose an improved simulated annealing algorithm with mutation (ISAM). Then the ISAM algorithm is introduced into the PSO algorithm to jump out the local optimum, effectively achieve the global optimum adjust and optimize the population, maintain the diversity of the population, improve the local search ability and convergence speed. Six classical functions are selected to test the performance of the proposed ISAMPSO algorithm. The simulation experiments results show that the proposed ISAMPSO algorithm can effectively overcomes the stagnation phenomenon and enhance the global search ability. The convergence speed and accuracy were better than the PSO algorithm.

Keywords: *Particle swarm optimization; mutation operator; simulated annealing algorithm; optimization; classical function*

1. Introduction

Particle swarm optimization (PSO) [1] algorithm was introduced by Kennedy and Eberhar in 1995. The PSO algorithm is a population-based search algorithm based on the simulation of the social behavior of birds or fishes within a flock. It takes on these characteristics of the easy describing and realization, the rarely adjusting parameters, the relatively smaller population, less number of function evaluations, fast convergence speed, parallel processing and robustness. It can find the global optimal solution of the solving problem with larger probability, and the calculation efficiency is higher than traditional random methods. The PSO algorithm has profound intelligent background, and is suitable for scientific research and engineering application) [2]. Therefore, the PSO algorithm has been aroused widespread concern in evolutionary computation research field. And a large number of research results are obtained in a few years. It has been successfully applied in function optimization, neural network training, fuzzy control system, classification, pattern recognition, signal processing, robot technology and so on [3-5].

Compared to other evolutionary algorithms, the PSO algorithm has great advantages in solving the problem of high dimension and complex. However, the PSO algorithm likes other intelligent optimization algorithms, it is also easy to fall in the local extreme points, slow convergence speed in the later evolution, lost diversity and poor optimization accuracy. So many researchers have proposed a large number of improved algorithms, which improve the performance of the basic PSO algorithm on some extent. Shi *et al*. [6]

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presented a variable population-size genetic algorithm (VPGA) by introducing the "dying probability" for the individuals and the "war/disease process" for the population. Tang *et al*. [7] presented a simulated annealing particle swarm optimization algorithm (SA-PSO) to solve the complicated and nonlinear generation expansion planning of hydro-thermal power system (include nuclear plant). Kim and Hirota [8] presented a genetic algorithm-particle swarm optimization (GA-PSO) algorithm based on vector control for loss minimization operation of induction motor. Li *et al*. [9] presented a new evolutionary learning algorithm based on a hybrid of improved real-code genetic algorithm (IGA) and PSO algorithm, called HIGAPSO algorithm. Niknam *et al*. [10] presented a hybrid evolutionary programming based clustering algorithm, called PSO-SA, by combining PSO and SA. Neoh *et al*. [11] presented a layered encoding cascade evolutionary approach to solve a 0/1 knapsack optimization problem, and a layered encoding structure based on the schema theorem and the concepts of cascade correlation and multi-population evolutionary algorithms. Behnamian and Fatemi Ghomi [12] presented a PSO-SA hybrid metaheuristic based on combining the advantages of PSO and SA for a new comprehensive regression model to time-series forecasting. Lee and Hsiao [13] adopted the S-system model to represent the gene network and esTablelish a methodology to infer the model. And an adaptive genetic algorithm-particle swarm optimization hybrid method is proposed to infer appropriate network parameters. Thanushkodi and Deeba [14] presented a variant of PSO, which is hybridized with the simulated annealing approach to achieve better solutions. Rahim *et al*. [15] presented a hybrid particle swarm and genetic algorithm based on discrete augmented Lagrangian approach to achieve the optimal value of Lagrange multipliers and required parameters. Soleymani [16] presented a new method that uses the combination of PSO and SA to predict the bidding strategy of Generating Companies (Gencos) in an electricity market where they have incomplete information about their opponents and market mechanism of payment is pay as bid. Tajbakhsh *et al*. [17] presented a very fast hybrid metaheuristic algorithm based on combining PSO and SA. Wang *et al*. [18] presented a simulated annealing particle swarm (PSO-SA) algorithm for solving the shortest path on curved surface. Lee and Ponnambalam [19] presented two evolutionary heuristics to determine the cutting parameters in multipass turning operations. Sheikhalishahi *et al*. [20] presented a novel hybrid GA- PSO approach for reliability redundancy allocation problem (RRAP) in series, series-parallel, and complex (bridge) systems. Galvez and Iglesias [21] presented a novel hybrid evolutionary approach (called IMCHGAPSO) for B-spline curve reconstruction comprised of two classical bio-inspired techniques: GA and PSO, accounting for data parameterization and knot placement, respectively. Pan and Das [22] presented a new hybrid regrouping PSO-GA approach to design sub-optimal state feedback regulators over networked control systems with random packet losses. Rabbani *et al*. [23] presented a new hybrid GA-PSO metaheuristic algorithm to be applicable and reliable comparing its numerical results with GAMS. Wang *et al*. [24] presented a new PSO-SA algorithm, which focuses on researching the effect of inertia weight of PSO-SA algorithm on the performance of the algorithm. Khoshahval *et al*. [25] presented a new parallel optimization (P-PSOSA) algorithm for performing the fuel management optimization. Two different fitness function considering the multiplication factor maximizing and power peaking factor minimizing objectives are simultaneously defined. Martínez-Soto *et al*. [26] presented a hybrid PSO-GA optimization method for automatic design of fuzzy logic controllers (FLC) to minimize the steady state error of a plant's response. Sahoo *et al*. [27] presented an efficient hybrid approach based on genetic algorithm and particle swarm optimization for solving mixed integer nonlinear reliability optimization problems in series, series-parallel and bridge systems. Sarasvathi *et al*. [28] presented a hybrid PSO-GA based on integrating the strength of PSO and GA to find the routing with QoS satisfied and an interference free path from the redundant paths. Tao *et al*. [29] presented an improved particle swarm algorithm (SA-PSO) to solve this problem, which can restrict the position change of original and new particles in the iteration process and accelerate the convergence speed of the algorithm.

The SA algorithm is a computational stochastic technique for obtaining near global optimum solutions to the complex optimization problems. It is inspired from the thermodynamic process of annealing of molten metals to attain the lowest free energy state. And the mutation operator can randomly change value of individual genes in order to take on the diversity of individuals in the population for guiding the search. So the idea of SA algorithm and mutation operator are introduced into the particle swarm optimization algorithm to propose an improved PSO(ISAMPSO) algorithm based on the mutation operator and simulated annealing in this paper. The ISAMPSO algorithm combines the global search optimization ability and simple realization of PSO algorithm with stronger jumping out of local optimal solution ability of SA algorithm and guiding the search ability of mutation operation in order to avoid falling into local extreme point of PSO algorithm and improve the convergence speed and accuracy of ISAMPSO algorithm in the late evolution.

The rest of this paper is organized as follows. Section 2 briefly introduces particle swarm optimization (PSO) algorithm. Section 3 briefly introduces mutation operator and simulated annealing (SA) algorithm. Section 4 presents an improved PSO (ISAMPSO) algorithm based mutation operator and simulated annealing (SA) algorithm. In this section, the idea and the steps of the ISAMPSO algorithm are introduced in detail. Section 5 applies the ISAMPSO algorithm for solving several benchmark functions. Finally, the conclusions are discussed in Section 6.

2. Particle swarm Optimization (PSO) Algorithm

The PSO algorithm [1] is a population-based search algorithm based on the simulation of the social behavior of birds within a flock. In PSO algorithm, individuals, referred to as particles, are “flown” through hyper dimensional search space. The particles’ positions within the search space are changed based on the social-psychological tendency of individuals in order to delete the success of other individuals. The changing of one particle within the swarm is influenced by the experience, or knowledge. The consequence of modeling for this social behavior is that the search is processed in order to return toward previously successful regions in the search space. Namely, the velocity(v) and position(x) of each particle will be changed by the particle best value (pB) and global best value (gB). The velocity and position updating of the particle is shown in the followed expression:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1 \left(pB_{ij}(t) - x_{ij}(t)\right) + c_2 r_2 \left(gB_{ij}(t) - x_{ij}(t)\right) \quad (1)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (2)$$

Where $v_{ij}(t+1)$, velocities of particle i at iterations j, $x_{ij}(t+1)$, positions of particle i^{th} at iterations j^{th}. w is inertia weight to be employed to control the impact of the previous history of velocities. Accordingly, the parameter w regulates the trade-off between the global and local exploration abilities of the swarm.

The basic flow chart of PSO algorithm is shown in Figure1.

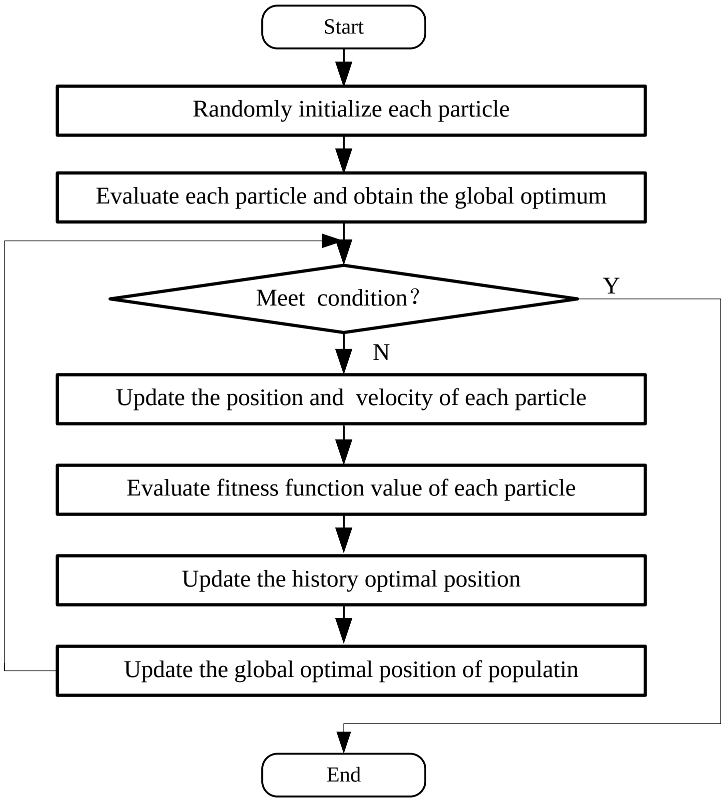

Figure 1. The Basic Flow Chart of PSO Algorithm

3. Mutation Operator and Simulated Annealing (SA) Algorithm

3.1. Mutation Operator

The crossover operation plays a vital role in genetic algorithm. But it only permutes and combines the existing genes, so new genes cannot be generated. With the further search, the individuals in the population have local similarity, which will result in the failure crossover, make the search in the stagnation state, fall into the local optimal solution, namely the premature phenomenon. At this time, the mutation operation is particularly important. The mutation operator can randomly change value of individual genes to take on the diversity of individuals in the population, which guide the search, and have the chance to climb the mountain and converge to the global optimum. So the mutation operation is the most important means to guide the search to climb mountain and prevent the convergence before the mature.

3.2. Simulated Annealing (SA) Algorithm

The basic idea of SA algorithm comes from the physical annealing principle [30]. The object particles move in disorder at high temperature, and the particles can converge to a lowest energy state when the temperature gradually decreases. The purpose of converging to the optimal solution is realized. First, the SA algorithm generates a random solution on the problem solution space, which is disturbed. Then the state transfer process of the solid particle under a certain temperature is simulated. The obtained solutions by disturbing is evaluated, and the solution is compared with the current solution and replaced according the Metropolis criterion. The SA algorithm repeats disturbing under the same temperature in order to simulate all kinds of energy states in the solid. In addition, the SA algorithm imitates the decreasing process of temperature by changing its parameters until the temperature reaches a given value. At this time, the obtained solution is regarded as the final solution, which is equivalent to the lowest energy state. When the SA algorithm is used to solve the optimization problem, the basic flow chart is shown in Figure2.

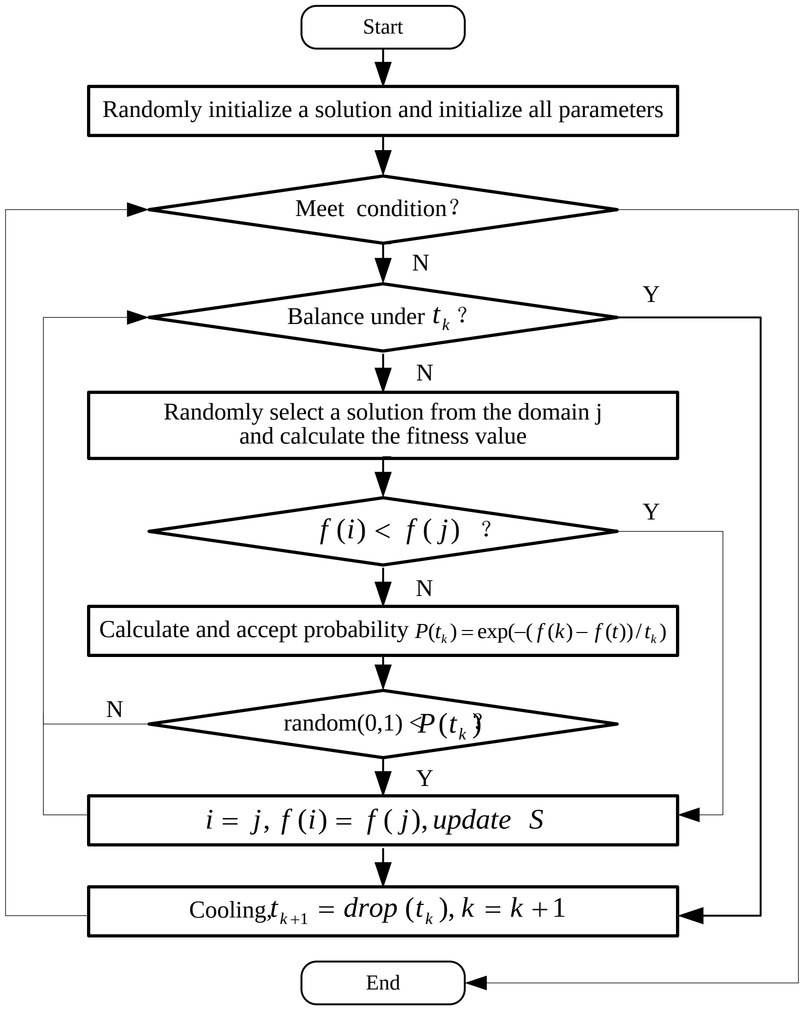

Figure 2. The Flow of the SA Algorithm

The core theory of the SA is to allow the occasional worsening moves, so that these can eventually help locate the neighborhood to the global minimum. The associated expression of the probability is given by the Boltzmann:

$$probability(p) = \exp(\frac{-\Delta E}{K_b T}) \tag{3}$$

In the expression (3), K_b is a constant, ΔE is the change in the energy value from one point to the next, T is the temperature.

For the optimization the energy term, ΔE refers to the value of the e function, T is a control parameter that regulates the process of annealing. The acceptance criterion is popularly referred to as the Metropolis criterion. And the improving and deteriorating move of this acceptance criterion has been proposed by Galuber:

$$probability(p) = \frac{\exp(-\Delta E / T)}{1 + \exp(-\Delta E / T)} \tag{4}$$

4. An Improved PSO (ISAMPSO) Algorithm

The mutation operator is the most important methods to guide the search for climbing mountain and preventing the convergence. The SA algorithm unceasingly generates new solutions with solutions, and in accordance with the following criteria to determine whether to accept by using generation mechanism of new solution from an initial solution. And determine whether to accept a new solution according to Metropolis criterion. The generation of new solution is the most time-consuming step in SA algorithm, but it directly affects the search efficiency of solution space. The PSO algorithm based on mutation operator is often difficult to obtain the optimal solution with higher precision due to existing the visual and step randomness and random behavior. And the SA algorithm has the advantages of high quality, strong robustness of the initial value, the strong local search ability. However, it is suitable to combine different algorithms based on advantage complementary for finding a method to solve this problem. So an improved PSO (ISAMPSO) algorithm based on the satisfactory solution of fast found global extreme value of the mutation operator and strong local search ability of simulated annealing under low temperature in this paper. In the ISAMPSO algorithm, the mutation operator of genetic algorithm is introduced into the SA algorithm as a generation mechanism of new solution in order to propose an improved simulated annealing algorithm with mutation (ISAM). Then the ISAM algorithm is introduced into the PSO algorithm to jump out the local optimum, effectively achieve the global optimum adjust and optimize the population, maintain the diversity of the population, improve the local search ability and convergence speed. So the ISAMPSO algorithm takes on strong global search ability and local search ability.

The steps of the proposed ISAMPSO algorithm are obtained as follows:

Step1. Initialize

Randomly generate population(m),the velocity and position of each particle is initialized. Set the cognition learning factor (c_1), social learning factor(c_2),inertia weight(ω), the number of maximum iteration($G_{\max}$),initial acceptance probability (P_r).

Step2. Calculate the fitness value

According to the objective optimization problem, the fitness value of each individual is calculated. The best position of particle is $Pbest$ and global best of population is $Gbest$.

Step3. Initialize the annealing temperature

$$T_0 = \frac{f_{\min}^0 - f_{\max}^0}{\ln P_r} = -\frac{|\Delta f|}{\ln P_r} \tag{5}$$

Step4. Determine

Determine whether the termination condition is meet. If the termination condition is meeting, go to **Step 11**. Otherwise, go to **Step 5**.

Step5. Calculate the fitness of each particle($f_i(k)$) and the average fitness($f_{avgi}(k)$).

Step6. If the fitness of particle is better than $Pbest$, the current fitness is set as $Pbest$. The optimal individual extreme value is selected as $Gbest$.

Step7. Update the position and velocity of the particles

Step8. Calculate the fitness of each particle($f_i(k+1)$) and the average fitness($f_{avgi}(k+1)$).

Step9. The mutation operator is used to generate the new mutation.

Step10. Determine whether to accept a new solution.

Calculate the caused change amount of fitness value between two positions $\Delta f = f_i(k+1) - f_i(k)$. If $\Delta f < 0$, a new solution is accepted. Otherwise it will remain the old solution.

Step11. Output the optimal solution.

5. Experimental Results and Analysis

In order to test the optimization performance of the proposed ISAMPSO algorithm for solving complex problem, several benchmark functions (Rastrigrin, Schaffer's f6, Sphere, Rosenbrock, Griewank) are selected in this paper. The PSO algorithm and SAPSO algorithm are select to compare with the proposed ISAMPSO algorithm. The parameters of the algorithms are selected after testing. We started with some classic values that have already been used in other studies papers, and then we modified these values until the selected values are chosen. The selected ones are those that gave the best computational results concerning both the quality of the solution and the run time needed to achieve this solution. The parameters of three algorithms are given in Table.1. The experiment environment are: the Pentium IV, 2.0GB RAM, Matlab 2012b. Several benchmark functions are shown Table. 2.

Table 1. The Parameters of Three Algorithms

Parameters	PSO	SAPSO	ISAMPSO
Population size(m)	60	60	60
Iteration times($G_{\max}$)	1000	1000	1000
inertia weight(w)	0.80	0.80	0.80
Max velocity(v)	100	100	100
Cognition learning factor(c_1)	c_1 =2	c_1 =2	c_1 =2
Social learning factor(c_2)	c_2 =2	c_2 =2	c_2 =2
Initial temperature(T_0)	N/A	15	15
Initial acceptance probability (P_r)	N/A	P_r =0.7	P_r =0.7
Mutation probability (P_m)	N/A	0.1	0.1

Table 2. Benchmark Functions

Function	Function Expression	Opt.	Dim.	Range
Rastrigrin	$f_1(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	**0**	**30**	$(-10,10)^n$
Schaffer's f6	$f_2(x)=\frac{(\sin(\sqrt{x_2+y_2}))^2-0.5}{(1.0+0.001(x^2+y^2))^2}+\frac{1}{2}$	**0**	**2**	$(-100,100)^2$
Sphere	$f_3(x)=\sum_{i=1}^{n}x_i^2$	**0**	**30**	$(-100,100)^n$
Rosenbrock	$f_4(x)=\sum_{i=1}^{n-1}100(x_{i+1}-x_i^2)^2+(x_i-1)^2$	**0**	**30**	$(-100,100)^n$
Griewank	$f_5(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2+\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	**0**	**30**	$(-600,600)^n$

For each benchmark function, all algorithms are independently run 50 times. The solution quality with the optimal value and mean value and optimization rate are reported in Table. 3.

Table 3. The Experiment Results

Function	Opt.	Algorithm	Optimal value	Mean value	Optimization rate
Rastrigrin	**0**	**PSO**	3.580 245E-008	1.068 253E-006	16%
		SAPSO	8.352 534E-030	4.681 685E-028	57%
		ISAMPSO	**5.566 083E-038**	6.350 471E-036	62%
Schaffer's f6	**0**	**PSO**	2.780 467E-004	5.183 503E-003	10%
		SAPSO	6.903 523E-027	3.640 489E-025	95%
		ISAMPSO	**3.340 436E-031**	6.814 609E-030	**100%**
Sphere	**0**	**PSO**	3.403 257E-014	4.253 402E-013	86%
		SAPSO	5.057 492E-044	3.471 071E-041	93%
		ISAMPSO	**2.768 504E-050**	8.671 650E-046	**100%**
Rosenbrock	**0**	**PSO**	1.463 467E-003	5.052 562E-003	5%
		SAPSO	4.523 708E-004	2.562 052E-003	78%
		ISAMPSO	5.056 682E-005	2.351 491E-004	86%
Griewank	**0**	**PSO**	7.527 803E-004	2.541 960E-003	88%
		SAPSO	3.602 792E-008	6.046 251E-007	86%
		ISAMPSO	4.131 064E-010	1.053 592E-008	**96%**

As can be seen in Table.3, the proposed ISAMPSO algorithm can obtain better optimization results than the PSO algorithm and SAPSO algorithm for Rastrigrin, Schaffer's f6, Sphere, Rosenbrock and Griewank. And the obtained optimal solution is very close to the global optimal value for Sphere, Rastrigrin and Schaffer's f6. And for the performance of optimization rate, the proposed ISAMPSO algorithm can obtain higher optimization rate than the PSO algorithm and SAPSO algorithm for all given benchmark functions. For Schaffer's f6 and Sphere functions, the optimization rates of the proposed ISAMPSO algorithm are 100%. So the proposed ISAMPSO algorithm significantly outperforms the PSO algorithm and SAPSO algorithm for all given benchmark functions. In a word, the proposed ISAMPSO algorithm can offer the higher solving accuracy than the PSO algorithm and SAPSO algorithm for all given test functions.

6. Conclusion

In allusion to the unbalanced global and local search ability, slow convergence speed and solving accuracy of the PSO algorithm, an improved simulated annealing (ISAM) algorithm based on mutation operator is introduced into the PSO algorithm with crossover and Gauss mutation to propose an improved PSO (ISAMPSO) algorithm in this paper. Because the mutation operator is the most important methods to guide the search for climbing mountain and preventing the convergence, it is introduced into the SA algorithm as a generation mechanism of new solution in order to propose an improved simulated annealing (ISAM) algorithm, which is introduced into the PSO algorithm to jump out the local optimum, effectively achieve the global optimum adjust and optimize the population, maintain the diversity of the population, improve the local search ability and convergence speed. Several benchmark functions (Rastrigrin, Schaffer's f6, Sphere, Rosenbrock, Griewank) are selected to test the optimization performance of the proposed ISAMPSO algorithm for solving complex optimization problem. The experiment results show that the proposed ISAMPSO algorithm can effectively overcomes the stagnation phenomenon and enhance the global search ability.

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