A LH-DM Strategy Based Particle Swarm Optimization Algorithm

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***Abstract*--Aiming at the premature problem of the Particle Swarm Optimization (PSO), an improved algorithm based on dynamic mutation strategy named Lowdiversity and Highdiversity Dual Mutation Factors Particle Swarm Optimization (LH-DMPSO) was proposed. The dynamic mutation strategy enhanced particle diversity, avoid falling into local optimal position, simulation results based on the Benchmark functions shows that the improved algorithm exceeds the standard PSO and Gaussian Mutation Particle Swarm Optimization (GMPSO) on convergence and stability.**

Keywords-premature convergence; dynamic mutation; particle diversity

I. INTRODUCTION

Particle Swarm Optimization (PSO) [1] is a swarm intelligent algorithm proposed by the social psychologist Dr Kennedy and the Electronic Engineer Dr Eberhart in 1995. Because of its simplicity, fast convergence speed and advantages of less adjustable parameters, PSO is widely used in nonlinear function planning [2], power system [3], path planning problem [4] and so on. However, when solving complex nonlinear optimization problem, PSO is easy to fall into the premature convergence problem. In order to deal with this shortcoming, many solutions were proposed. A. Ratnaweera [5] has proposed a linear variation of the acceleration factor strategy, which the cognitive factor linear decline, while social factors linear increase during the search process. R. K. Ursem [6] has proposed a diversity guided strategy to control the swam moving. By measuring the diversity he let the swarm alternate between attraction and repulsion phases.

In this paper, we present an improved scheme to deal with the problem. we proposed a dynamic mutation strategy based on the average particle distance to maintain the swam diversity and so as to solve the premature issue. Tests on the selected four Benchmark functions show that our algorithm has better search performance than standard PSO and Gaussian mutation particle swarm optimization (GMPSO).

II. PARTICLE SWARM OPTIMIZATION

In the Particle Swarm Optimization, each particle can be viewed as a solution to the problem in the feasible space. All particles constantly adjust their status through tracking the global best position gbest and each particle's historical best position pbest_i, so as to complete the search process.

Suppose that the swam composed of M particles. Position vector of i'th particle : $x_i = (x_{i1}, x_{i2}, ..., x_{iD}), 1 \le \mathrm{i} \le \mathrm{M}$,velocity vector of i'th particle: $v_i = (v_{i1}, v_{i2}, ..., v_{iD}), 1 \le \mathrm{i} \le \mathrm{M}$, the i'th particle's historical best position: $pbest_{i1}, pbest_{i2}, ... pbest_{iD}$, the swarm's best position: $gbest$,f(x) is the fitness function, then the i-the particle's current historical best position determined by the following formula (1).

$$pbest_i(\mathrm{k}+1) = \begin{cases} pbest_i(\mathrm{k}), \text{if } \mathrm{f}(\mathrm{x_i}(\mathrm{k}+1)) \ge \mathrm{f}(pbest_i(\mathrm{k})) \\ x_i(\mathrm{k}+1), \text{if } \mathrm{f}(\mathrm{x_i}(\mathrm{k}+1)) < \mathrm{f}(pbest_i(\mathrm{k})) \end{cases} \quad (1)$$

The swarm's best position gbest determined by the following formula (2).

$$gbest = \min\{\mathrm{f(pbest_1), f(pbest_2), f(pbest_3), ..., f(pbest}_m)\} \quad (2)$$

At each step, all particles update their position and velocity vector, as in the formula (3) and (4).

$$\mathrm{v_{id}^{k+1} = w^*v_{id}^k + r_1{}^*c_1{}^*\left(pbest_{id}^k - x_{id}^k\right) + r_2{}^*c_2{}^*\left(gbest_d^k - x_{id}^k\right)} \quad (3)$$

$$\mathrm{x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1}} \quad (4)$$

where, i is the i'th particle, d is the dimension of search space, k is the number of iterations. $\mathrm{r_1, r_2}$ are random numbers, usually [0,1], c_1, c_2 are acceleration factor, the parameter w is the inertia weight and controls the step magnitude. Once the particles are constraint by a local extreme value, the swarm falls into premature convergence problem.

III. LH-DM PARTICLE SWARM OPTIMIZATION

Reference [7] found that the premature problem was closely related to the population diversity, the population diversity will decline with the progress of the algorithm. In this paper , we first introduce the dual mutation factors [8] to tracing the best particle and the worst particle respectively ;then we propose a diversity-guided dynamic mutation to maintain the population diversity, and then avoid the premature problem.

A. Average Particle Distance

Reference [9] proposed to use average particle distance to measure the population diversity:

$$diversity(\mathrm{m}) = \frac{1}{|m|*|L|} * \sum_{i=1}^{|m|} \sqrt{\sum_{j=1}^{D} (\mathrm{p_{ij}} - \overline{p_j})^2}, \overline{p_j} = \frac{1}{N} \sum_{i=1}^{m} \mathrm{p_{ij}} \quad (5)$$

where, m is the swarm, $|m|$ is the swarm size, $|L|$ is the length of longest the diagonal in the search space, D is the dimension of the problem. Diversity (m) has measured the swarm average distance to the swarm center. it is independent of swarm size, the dimensionality of the problem as well as the search range in each dimension. Smaller diversity (m) means the distribution of the particles is more concentrated and is more easy to fall into local optimal value, conversely can achieve a more dispersed distribution and avoid this problem by a large probability.

B. Dual Mutation Factors

Dual Mutation Factors are consist of the variables Ybest and Yworst. the best factor Ybest is used to trace the particle with best fitness value, accordingly, the worst factor Yworst is used to trace the particle with worst fitness value. In each iteration, we execute mutation according to formula (6) on the best particle which Ybest traced so that the best particle will be guided to search near current global best position and improve the accuracy of the result. Conduct mutation according to formula (7) on the worst particle which Yworst traced so that the worst particle can search a new area far from the current global best position and improve the Average Particle Distance (APD).

$$X = Yworst * (1 + 0.618 \,\mathrm{randn}) \qquad (6)$$

$$X = Ybest * (1 + 0.5 \,\mathrm{randn}) \qquad (7)$$

where randn is the random number generated according to the Gaussian probability distribution, i.e. N(0,1).

C. LH-DM Strategy

In this paper, we propose a dynamic mutation strategy according to the changes of the average particle distance. When diversity(m) is lower than the preset Lowdiversity, execute formula (6); when diversity(m) is higher than the preset Highdiversity, execute formula (7).

Lowdiversity and Highdiversity Dual Mutation Factors (LH-DM) strategy:

if diversity(m)< Lowdiversity
execute formula (6);
if diversity(m)> Highdiversity
execute formula (7);

which, Lowdiversity and Highdiversity are preset minimum and maximum threshold values according to the complexity of the fitness function,we refer to the reference [6] set Lowdiversity=$5.0 * 10^{-6}$, Highdiversity=0.25.

D. LH-DMPSO

The proposed algorithm description is presented below:

1. parameters setting, initialize each particle's position vector and velocity vector;
2. initialize each particle's $pbest_i$ and the swarm's gbest according to formula (1) and formula (2) respectively, setting the best particle's position as Ybest, worst particle's position as Yworst;
3. calculate divsersity(m) according to formula (5), execute mutation according to formula (6), formula (7);
4. update each particle's velocity vector according to formula (3);
5. update each particle's position vector according to formula (4);
6. calculate each particle's fitness, then update $pbest_i$, gbest, Ybest, Yworst;
7. Iteration from step 3 until reaching the final stop.

IV. SIMULATION RESULTS

In order to test the performance of LH-DMPSO, we conduct simulations compared with the Standard particle swarm optimization (PSO) and Gaussian mutation particle swarm optimization (GMPSO) on four Benchmark functions.

A. Benchmark Functions

The LH-DMPSO has been tested on four different functions:

Function	Expression	Defined field	Optimal solution
Sphere	$f(x) = \sum_{i=1}^{n} x_i^2$	[-100, 100]	0
Ackley	$f(x) = -20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}) - \exp(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i) + 20 + e$	[-5, 5]	0
Griewangk	$f(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600, 600]	0
Rastrigrin	$f(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	[5. 12, 5. 12]	0

B. Results and Discussion

Parameter settings: Three algorithms parameter setting are basically the same. Population size m=50, Dimension sizes: 10, 20 and 30, w=1.412413, The maximum number of generations N=5000, The accelerating constants c_1=2 and c_2=2, target optimal fitness value is set to $1.0 * 10^{-5}$. Such running trials were repeated for each of the chosen function for 50 times. The experimental results are presented in Table 1~4. Dim is dimension of search space, Avebest is the average best fitness value of 50 tests. Aveiter is the average iterations when reach the target optimal fitness, '—' means search failure. Ras means algorithm success rate.

TABLE I. THE RESULTS OF THE TIRALS

Function	Dim	PSO			GMPSO			LH-DMPSO		
		Avebest	Aveiter	Ras	Avebest	Aveiter	Ras	Avebest	Aveiter	Ras
Sphere	10	3.63×10^{-7}	423.72	50/50	6.72×10^{-11}	217.23	50/50	0	213.21	50/50
	20	0.2231	637.24	0/50	9.13×10^{-9}	353.11	50/50	2.15×10^{-11}	335.43	50/50
	30	1.0772	—	0/50	2.32×10^{-8}	381.46	50/50	3.47×10^{-9}	365.22	50/50

TABLE II. THE RESULTS OF THE TIRALS

Function	Dim	PSO			GMPSO			LH-DMPSO		
		Avebest	Aveiter	Ras	Avebest	Aveiter	Ras	Avebest	Aveiter	Ras
Ackley	10	0.0053	467.21	50/50	3.37×10^{-6}	286.21	49/50	1.23×10^{-11}	245.72	50/50
	20	0.2871	—	0/50	9.12×10^{-6}	374.91	46/50	5.33×10^{-9}	335.23	50/50
	30	1.103	—	0/50	1.03×10^{-5}	494.53	35/50	7.86×10^{-8}	416.77	50/50

TABLE III. THE RESULTS OF THE TIRALS

Function	Dim	PSO			GMPSO			LH-DMPSO		
		Avebest	Aveiter	Ras	Avebest	Aveiter	Ras	Avebest	Aveiter	Ras
Griewangk	10	0.1041	—	0/50	0.0867	486.21	15/50	1.01×10^{-5}	324.77	50/50
	20	0.2035	—	0/50	0.1411	633.96	11/50	0.97×10^{-4}	613.09	50/50
	30	1.0261	—	0/50	0.9731	—	0/50	9.21×10^{-4}	1103.11	38/50

TABLE IV. THE RESULTS OF THE TIRALS

Function	Dim	PSO			GMPSO			LH-DMPSO		
		Avebest	Aveiter	Ras	Avebest	Aveiter	Ras	Avebest	Aveiter	Ras
Rastrigrin	10	6.3713	—	0/50	5.07×10^{-6}	413.51	50/50	7.63×10^{-9}	373.22	50/50
	20	15.5246	—	0/50	1.64×10^{-4}	583.73	37/50	6.87×10^{-7}	516.41	50/50
	30	54.7634	—	0/50	0.0937	—	0/50	0.17×10^{-3}	1469.15	31/50

From the results obtained, it can be observed that for the four benchmark minimization problems, compared to PSO and GMPSO, LH-DMPSO can achieve better search per-formance. For Sphere function, when the search space is 10 dimension, the average best fitness value algorithm can converge to 0 using LH-DMPSO, for the three multi peak functions Ackley, Griewangk and Rastrigrin, LH-DMPSO can obtain a smaller average best fitness value, means that the proposed algorithm can achieve good performance when solving high dimension, multi peak problems. Further more, analysis the average iterations of each table, LH-DMPSO is smaller than the standard PSO and GMPSO, means that the proposed algorithm can converge to the target value faster. Finally analysis the Ras in table 1~4, LH-DMPSO has the highest success rate, means a higher stability.

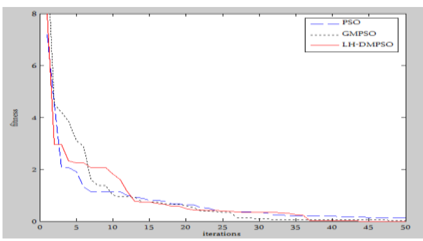

FIGURE I. M=50, DIM=20 RESULT FOR SPHERE FUNCTION

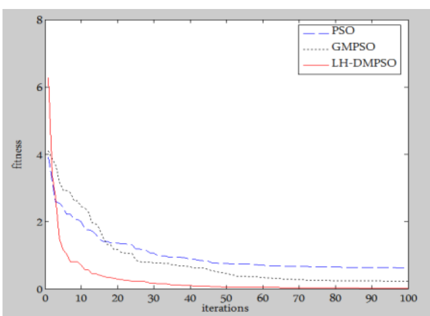

FIGURE II. M=50, DIM=30 RESULT FOR ACKLEY FUNCTION

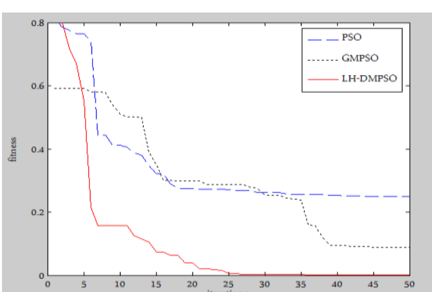

FIGURE III. M=50, DIM=10 RESULT FOR GRIEWANGK FUNCTION

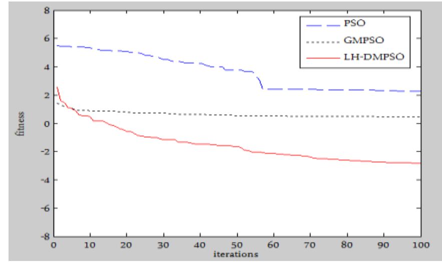

FIGURE IV. M=50, DIM=30 RESULT FOR RASTRIGRIN FUNCTION

Figure 1~4 shows a more intuitive comparison between the standard PSO, GMPSO and LH-DMPSO, it can be observed that for the four benchmark functions, the LH-DMPSO algorithm shows considerably better convergence than the standard PSO and GMPSO. The solid line represent for LH-DMPSO can get a smaller fitness function value; While for Sphere function shown in Figure 1, the proposed algorithm performance improvement is not obvious, mainly because, for Sphere function, it is relatively easy to find its global best position, using standard PSO and GMPSO can also get satisfactory results. However, for Figure 2~4, LH-DMPSO performs significantly better, verifies that the proposed algorithm can achieve a more satisfactory performance when solving high-dimensional and multi-peak problems.

V. CONCLUSIONS

In this paper, a LH-DMPSO has been proposed to solve the PSO premature problem. By introducing dynamic mutation, we can maintain the population diversity at a satisfactory level, so as to avoid falling into local optimal. Finally, we conduct tests on four typical Benchmark functions, simulation results show that our proposed algorithm can achieve a lower average best fitness value, especially when solving high dimension and multi peak problems.

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