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An Improved Self-adaptive Memetic Differential Evolution (DE) Algorithm ⋆

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Abstract

This paper proposes an improved self-adaptive memetic differential evolution algorithm(IMDE). In the aspects of population initialization and local search, the normal distribution model is introduced to improve the classic differential evolution algorithm in order to guarantees its higher optimizing efficiency and accuracy. The self-adaptive operators of mutation and crossover are introduced which not only improve the global convergence, but also guarantee the convergence speed of the algorithm. The simulation results show that IMDE has good global convergence and can avoid premature convergence effectively.

Keywords: Differential Evolution Algorithm; Memetic Algorithm; Self-adaptive Algorithm; Local Search Strategy

1 Introduction

Genetic algorithm is a kind of stochastic optimization algorithm which borrowed ideas from natural selection and natural biological genetic mechanism.Because of its simple principle, robust, and suitable for parallel computing etc, since 1975 J.Holland [1] introduced, the research of the genetic algorithm liked a raging fire. But genetic algorithm adopts binary coding, the biggest drawback of the code length is bigger. To many optimization problems ,other the coding methods may be more beneficial. Differential Evolution algorithm was proposed by Storn [2] in 1995 to solve the chebyshev polynomial problem. Differential evolution algorithm is an optimization algorithm based on the theory of swarm intelligence.Compared with the genetic algorithm, DE inherited the global search strategy based on the population.The floating-point coding , the simple variation operation based on difference and the greedy competition survival strategy reduce the complexity of the algorithm. The unique memory function of DE makes it adjust search strategy

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dynamically according to the current situation search, and have strong robustness and global search capability.

The balance of global search and local development ability is the key problem to improve the performance of the differential evolution algorithm searching. Huawei Wu etc [3] used the method of point set initializing individuals to maintain the diversity of population.In 2006, Brest J [4] put forward a JDE algorithm to , adaptive adjustments. Yue Tan etc [5] put forward a kind of chaotic local search strategy of differential evolution algorithm (CLSDE).By using chaos algorithm near the best individual conducting the local search, it made the algorithm jump out of the local optimum.

Memetic algorithm [6] inherited the strong global search ability of genetic algorithm, at the same time, the local search strategy of Memetic made good the poor local search capability of genetic algorithm. This paper changes the random initial population in standard differential evolution algorithm .The malpractices of population initialization algorithm is improved, and adds the adaptive operators for the dynamic adjustment. The memetic algorithm is introduced to achieve the balance of global search and local search.

2 Classic Differential Evolution Algorithm

The descriptions of classic differential evolution algorithm are as below:

$$\min f(x_1, x_2, ..., x_D).$$

$$s.t. x_j^L \le x_j \le x_j^U.$$

Among them: D is the solution space dimension.x_j^L ,x_j^U respectively expresses the upper and lower bounds of the jth part of the scope x_j . The process of classic differential evolution algorithm is as follows:

(1) BEGIN

(2) Initialize:

initial population with formula(1)

$$P_{i,j}^0 = rand(1) \times (x_{i,j}^U - x_{i,j}^L) + x_{i,j}^L \tag{1}$$

(3) individual evaluation

(4) determine the optimal target values x_{best}

(5) While(don't meet the end criteria)

(6) each individual of the population executes mutation with formula(2) and get the variation individual v_i^{G+1} .

$$v_i^{G+1} = x_{r1}^G + F(x_{r2} - x_{r3}) \tag{2}$$

(7) variation individual and the random individual of the population execute crossover

operation with formula (3)and get the test individual $u_{i,j}^{G+1}$

$$u_{i,j}^{G+1} = \begin{cases} v_{i,j}^{G} & \text{if}((rand(j) \le CR) or (j = rnbr)), \\ x_{i,j}^{G+1} & \text{otherwise.} \end{cases} \tag{3}$$

(8) evaluate the target value of the test individual according to the objective function

(9) test individual and the individual of the population execute the greedyselection operation with formula(4) ,and get the offspring x_i^{G+1}

$$x_i^{G+1} = \begin{cases} x_i^{G} & \text{if}(f(u_i^{G+1}) \ge f(x_i^{G}), \\ u_i^{G+1}) & \text{otherwise.} \end{cases} \tag{4}$$

(10) update x_{best}

(11) End While

(12) output x_{best} and the corresponding objective function value

(13) END

3 Improved Differential Evolution Algorithm

3.1 Population initialization

The quality the optimum of differential evolution algorithm depends on whether the initial population contains all possible solutions within the solution space, and insures that the good individual don't lose in the evolutionary process. This shows that the initial population can neither rough random generate, nor traverses all conditions.Especially for the multivariate problems, as long as the algorithm takes the most representative individual of the solution space as the initial population, it can better reflect the inherent characteristics of the solution space.The algorithm of this paper uses the normal distribution method generating the initial population, and every time produce a individual. This method in a certain extent increases the possibility of the optimal to be selected, and can improve the optimization ability of the algorithm. The formula is as follows:

$$P_{i,j}^{0} = randn(1) \times (x_{i,j}^{U} - x_{i,j}^{L}) + x_{i,j}^{L} \tag{5}$$

Among them,$randn(1)$ generates the random numbers which obey $N(0, 1)$. The random distribution scatter-plot and normal distribution scatter-plot of the population individual are as shown in figure 1 and figure 2.

3.2 Adaptive operators

Scaling factor in a certain degree of the evolution controls the direction of the population and have a certain degree of control in the global search and local search ability of the algorithm. Yuelin Gao [7] thought that F was neither too big, nor less than a particular value.He advised that when $F \in [0.5, 1]$, the algorithm can get good results. Liqiang Jiang[8]studied the zoom factor value strategies of DE.The simulation results showed that with the increase of the number of iteration gradually reduce is helpful to improve the algorithm convergence rate. Amin Nobakhti etc[9] thought that the bigger CR was, the greater probability each dimension variation vector of the test vector was selected.So that the test vector relative to target vector was more perturbation, and reduced the algorithm convergence speed. Conversely,CR was small ,the population would rapid loss of diversity. ZexiDeng [10]crossover probability factor CR should be with the increase of the iteration times increased gradually.In literature[11], F =0.5 was thought that most of the questions had better effect. In literature [12], $CR \in [0.3, 0.9]$ was advised.

In conclusion, and after tests this paper puts forward the following adaptive zoom factor and crossover probability factor:

$$F = \begin{cases} 0.9 \times (\frac{G-1}{G_{max}} - 1)^2 & \text{if}((G < G_{max}) and (F \in [0.5, 1])), \\ 0.5 & \text{otherwise.} \end{cases} \tag{6}$$

$$CR = \begin{cases} 0.9 \times (\frac{G-1}{G_{max}} - 1)^2 & \text{if}((G < G_{max}) and (CR \in [0.3, 0.9])), \\ 0.5 & \text{otherwise.} \end{cases} \tag{7}$$

Among them, G expresses the iteration times; G_{max} expresses the maximum iteration times.

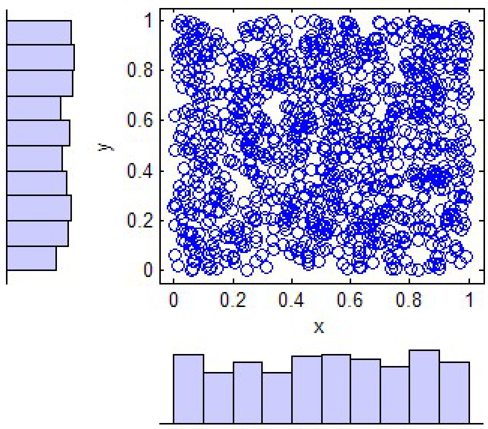

Fig. 1: The scatter-plot chart of random distribution

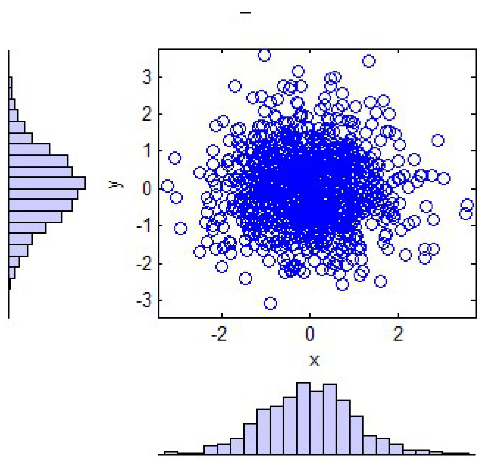

Fig. 2: The scatter-plot chart of normal distribution

3.3 Local search strategies

Local search is one of the most important link of Memetic algorithm, is also one of the factors DE whether it can get the optimal solution. Local search strategy is a kind of approximate algorithm.Generally,it can give an acceptable good solution, but it is likely to be trapped in a local peak. The algorithm will be over at this point, and the result may be not a more ideal result. This paper adopted k times local search in the vicinity of individual which is randomly selected from the adjacent domain in probability p after the end of each iteration,and get the optimal solution x'_{best}. If x'_{best} is better than x_{best} , then the value of x'_{best} will replace with the value of x_{best} and be instead of a random population individual.End the search, or continue DE basic operations. Local search formula is as follows:

$$x'_{best} = x_{rand} + Normalrand(0, 1) \tag{8}$$

Among them, $Normalrand(0, 1)$ obeys the standard normal distribution that the expect is 0, the variance is 1.

Along with the increase of number of iterations, the diversity of the population decline is the root cause of premature. To judge whether the population stagnant or achieve optimal solution, this paper introduces aggregation level factor A .

$$A = \frac{\min(f(\bar{G}), f(x_b(G)))}{\max(f(\bar{G}), f(x_b(G)))} \tag{9}$$

In the formular,$A \in (0, 1)$,$f(\bar{G})$ expresses the average fitness value of the Gth iteration. $f(x_b(G))$ expresses the best fitness value of the Gth iteration. To a certain extent A reflects the degree of individual species aggregation.The higher A is , the greater the degree of aggregation of the population is, the lower the diversity of population will be, and the easier the population the premature phenomenon appears. When $f(x_b(G))$ is a invariable in three consecutive generations, and A is more than the predetermined threshold T , the population will be initialized again using formula (5). The flow chart of improved Memetic DE is as figure 3.

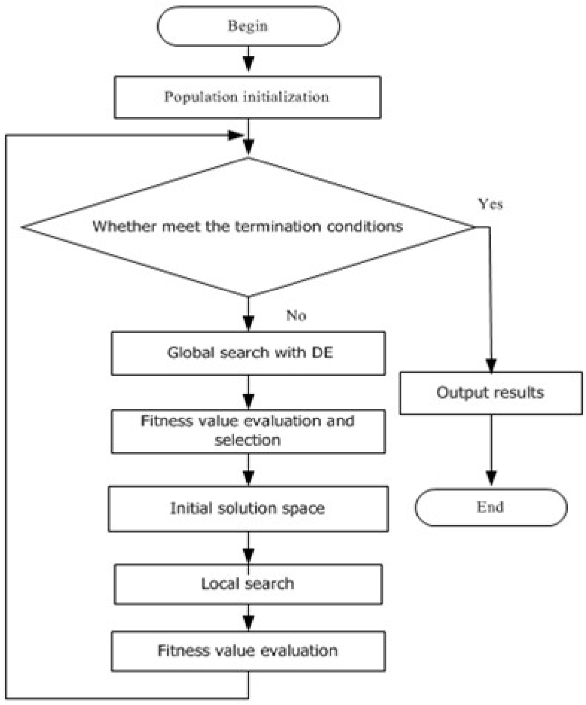

Fig. 3: The flow chart of improved Memetic DE

4 Numerical Experiments

In order to validate the efficiency of the proposed improved algorithm IMDE, this paper chooses four benchmarks functions : Griewank, Schwefel, Rosenbrock, Rastrigin. The related descriptions of the test functions see table 1.This paper chooses $DE/rand/1/bin$ to the optimal selection test, in order to compare the performance of imrproved Memetic Differential Evolution(IMDE). Test environment: Dell Vostro 1088 Windows XP, matlab R2010b.

Table 1: The description of typical benchmarks function

functions	function expressions	value range	dimension	peak types
Griewank	$f_1(x) = \frac{1}{4000}\sum_{i=1}^{n}(x_i)^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	$[-60, 60]$	30	multimodal
Schwefel	$f_2(x) = \sum_{i=1}^{n}(\sum_{j=1}^{i})^2$	$[-100, 100]$	30	multimodal
Rosenbrock	$f_3(x) = \sum_{i=1}^{n}[100 \times (x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	$[-30, 30]$	30	unimodal
Rastrigin	$f_4(x) = \sum_{i=1}^{n}[x_i^2 - 10 \times \cos(2\pi x_i) + 10]$	$[-5.12, 5.12]$	30	multimodal

4.1 Experimental setup

Experimental parameters Settings are shown in table 2. Except that the maximum iteration of f_1 is 1000, population size N_p of f_1 is 60 and the threshold of f_4 is 100.The zoom factor of Adaptive mutation Differential Evolution(ADE)is 0.6.The parameters options of other functions are shown in table 2.

Table 2: Parameters settings list

function names	expressions	parameter values
local search times	k	20
population scale	N_p	100
maximum iterations	$ITER$	2000
threshold	T	0.1
selection probability	$ITER$	0.8

4.2 Experimental results

The simulations pictures and the results are shown in figure 4 to 7 and table 3 .

The optimal results which are the best results are bold in table 3. From the table 3 and figure 4 to 7 it can see that the optimal results of f_1 to f_4 IMDE are better than the standard DE and ADE.For f_1 , the proposed algorithm IMDE can find the global optimal value(Note: In figure 4 the function optimization contrast image dont appear the line of IMDE. This explains that the optimal solutions are found in the first iteration).

From the simulation contrast results it can see that the searching capability of IMDE is superior to standard DE and ADE. It proves that the proposed algorithm IMDE are more effective for solving optimization problems.

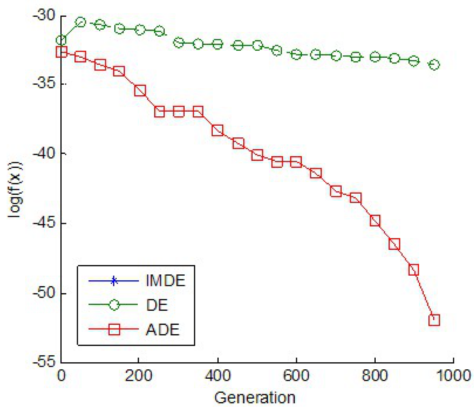

Fig. 4: The optimal curve of f_1

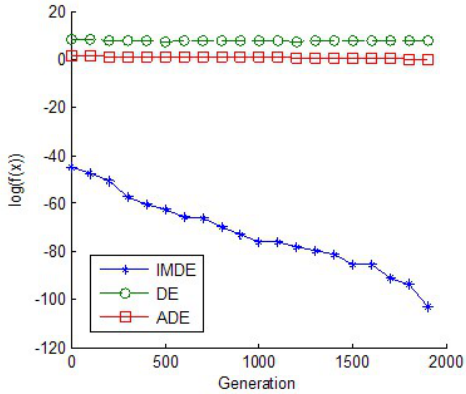

Fig. 5: The optimal curve of f_2

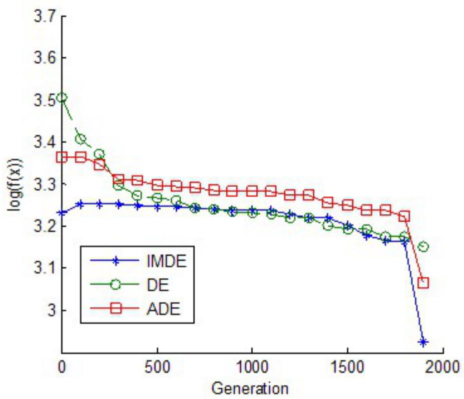

Fig. 6: The optimal curve of f_3

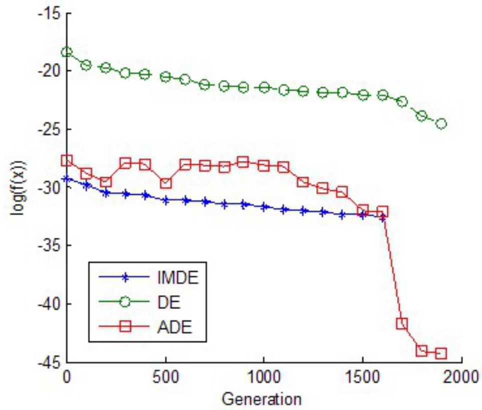

Fig. 7: The optimal curve of f_4

5 Conclusion

This paper puts forward a method which obeys normal distribution to initializing population based on the analyzes the existing advantages and disadvantages of DE, and improves the optimal algorithm efficiency and optimal precision. By using the strong local search ability, this paper an improved Memetic DE algorithm.So the balance of global search and local search of IMDE is realized.The adaptive operators on the adaptive adjustment of the population is introduced, and the algorithm convergence speed is improved.

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Table 3: Benchmarks functions test optimal results

functions	algorithms	minimum values	maximum values	average values	theory values
f_1	DE	2.6645e-15	1.4988e-14	1.5932e-14	0
	ADE	2.6878e-23	6.8834e-15	8.2812e-16	0
	IMDE	**0**	**0**	**0**	0
f_2	DE	1.5288e+03	3.2636e+03	2.4461e+03	0
	ADE	0.8654	5.7372	2.5049	0
	IMDE	**1.6436e-45**	3.1004e-20	**3.5631e-33**	0
f_3	DE	23.3955	33.256	25.99607	0
	ADE	21.4039	28.952	26.5218	0
	IMDE	**18.6243**	25.3124	24.1200	0
f_4	DE	2.3258e-11	1.0138e-08	1.2926e-09	0
	ADE	5.9878e-20	1.0214e-12	7.5231e-14	0
	IMDE	**0**	2.0111e-13	1.6414e-15	0

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