THE STUDY ON AN IMPROVED GENETIC ALGORITHM

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Abstract: By the analysis of the performance of binary encoding and real encoding and the characteristics of the optimization process, hybrid coding is proposed by combining binary encoding and real encoding. Hybrid coding synthesizes the advantage of both binary encoding and decimal encoding and maintains the accuracy of the algorithm. Accelerated operator based on line search is introduced to improve the searching speed of genetic algorithms. A hybrid coding genetic algorithm is proposed, which is used to solve nonlinear optimization problems. The results of simulation indicate that the new algorithm has good accuracy and capability of dealing with the constraints.

Keywords: hybrid coding, binary encoding, real encoding, accelerated operator, hybrid coding genetic algorithm(HCGA)

1. INTRODUCTION

Genetic algorithm, as an intelligent optimization method, has been proved theoretically and practically to have good rubustness. Genetic algorithm does not have much limitation of the objective functions(T Back, *et al.*, 1993; Rudolph G, *et al.*, 1997; Chellapilla K, *et al.*, 1998). Genetic algorithm has exerted good performance to solve complex nonlear optimization problems(Saleh, *et al.*, 2004; Lee, *et al.*, 2003; Tai, *et al.*, 2004; Hansen, *et al.*, 2004; Park, *et al.*,2003; Choi, *et all.*, 2002; Lyer, *et al.*, 2004). It is more effective than traditional mathematical optimization method in solving multidimensional problems. However, it has some defects as well. Premature convergence and low local search capability are both important matters in current study. A hybrid coding genetic algorithm is proposed in this paper. Binary encoding and real encoding are combined to synthesize the advantages of them and improve the performance of genetic algorithm. Based on the accelerated searching strategy of traditional optimization method, accelerated operator is introduced to enhance the searching speed. In addition, Gaussian mutation of variable step is applied to improve globle convergence of genetic algorithm.

2. HYBRID CODING MECHANISMS

Coding mechanisms of genetic algorithm are important factors that influence its performance. Binary encoding describes the variables simply, which makes the searching principle easily understood and provides powerful support for the development and improvement of the genetic algorithms. With the constant extension of the application field of genetic algorithms and penetrating study on genetic algorithms, some defects have been found in binary encoding, although its advantage has further been proved. Thus, a number of new coding mechanisms have occurred. Among them, real encoding is widely used in function optimization because of its direct expression and high accuracy. Studies have shown that binary encoding is superior to real encoding in global searching performance, but inferior to real encoding in population stability. Searching precision of binary encoding is limited by coding length, so real encoding is better than binary encoding in this aspect(Zhang Xiaohui, *et al.*, 1997).

Hybrid coding is proposed based on the study of binary encoding and real encoding. Concretely speaking, binary encoding and real encoding are associated and each is used in different searching phases. Firstly, binary encoding is used to exert its global searching capability and enable the algorithm to converge near to optimum solution rapidly. Secondly, real encoding is applied to gain global optimum solution with high precision, since it has a powerful local searching capability and good population stability. Binary encoding and real encoding are applied successively to perform rough searching and accurate searching, respectively. Description of variables and searching are both from rough to accurate, which fully exert the advantage of each coding mechanism.

3. ACCELERATED OPERATOR AND IMPROVEMENT OF MUTATION OPERATOR

Convergence speed of genetic algorithms is mainly up to genetic operator (eg. crossover operator, mutation operator). Traditional genetic operator has strongly randomcity and poor directivity. It can not guarantee that filial generation is better than parent. Thus, the convergence speed of genetic algorithms is affected. Besides, randomcity of genetic algorithms makes it difficult to find accurate solution. If the performance of genetic algorithms is to be improved, genetic operator of genetic algorithm should be improved.

Traditional optimal methods have good directivity and high convergence speed. Searching strategy of traditional optimal methods can be applied in genetic algorithms to enhance the convergence speed. So accelerated searching strategy is proposed based on traditional direct optimal methods. The main idea of it is that if the optimum solution is greatly improved compared to the initial solution after certain generations, the direction from the initial solution to the optimum solution can be regarded as a better searching direction. Searching can be performed in this direction to improve the present optimum solution. This strategy makes use of the available information in searching process and the idea of fall method so as to attain to the object of accelerated searching.

Based on the accelerated searching strategy, accelerated operator is introduced to genetic algorithm to improve the searching speed of genetic algorithms. Accelerated operator contains two parts. First, if the difference between the optimum value of a certain generation and the optimum value of former three generations exceeds a certain threshold:

$$\left|\frac{f^*(k-1)-f^*(k-3)}{f^*(k-1)}\right| \geq J \quad (k \geq 4) \tag{1}$$

Where $f^*(k)$ is optimum value of the k generations, J is threshold. The direction from the worse solution to the better solution can be regarded as an improved direction. So line search is performed in the direction of the two solutions:

$$f(x') = min\{f(x^* + \alpha P) | x^* + \alpha P \in R\} \tag{2}$$

The present optimum solution is replaced by the better one gained by line search. A certain individual in the present population is replaced by the optimal solution randomly. Second, two individuals of population are selected at random. Line search is performed from the direction from the inferior individual to the superior one. The individuals produced by accelerated operator become offsprings at pro rate just like the individuals produced by crossover operator and mutation operator. Since line search has obvious direction, the present optimum solution and selected individuals can generally be improved. Direct introduction of the individuals gained by line search to population can induce the information of better individual to searching process. Thus, accelerated operator can improve the searching efficiency and searching speed of genetic algorithm.

Chaotic mutation is widely used because of its initial value sensitivity and track ergodicity. Studies have shown that Gaussian mutation is as effective as chaotic mutation(Luo Chenzhong, *et al.*, 2000). Gaussian mutation is applied to improve the performance of genetic algorithms:

$$x'(k) = x(k) + \lambda(k)N(0,1) \tag{3}$$

Where $x(k)$ is individual of the $k$generations, $\lambda(k)$ is Gaussian mutation step, $N(0,1)$ is Gaussian stochastic variable.

Traditional Gaussian mutation step is a constant, which strongly influences the performance of mutation searching. Much larger step will affect searching precision and reduce searching efficiency and speed. Much shorter step will reduce the hill-climbing ability of genetic algorithm and can not keep the diversity of population, which will make the algorithm fall into local extreme value(Shi Tianyun, *et al.*, 2000).

Gaussian mutation of variable step is applied to improve the performance of mutation operator. Different step is used according to different phases. If the optimum value of neighboring generations does not change much, the step of Gaussian mutation will be increased properly to enlarge the search range forcibly, which will help to leap out of the local extreme value. If there is obvious change, step will be reduced to search in a smaller neighbourhood. In this case, neighbor search ability of Gaussian mutation is fully exerted so as to obtain accurate global optimum solution. Mutation step is defined by:

$$\lambda(k) = \begin{cases} \lambda(1 - |\dfrac{f^*(k-1) - f^*(k-3)}{f^*(k-1)}|), \\ \qquad \lambda = constant, \quad k \geq 4; \\ constant, \qquad\qquad 0 < k < 4 \end{cases} \quad (4)$$

4. SIMULATION STUDY

In order to test the performance of modified genetic algorithm proposed, the simulation study is performed for the following two typical nonlinear optimization problems.

test problem1.

$$\begin{aligned} min \quad & f(x) = (x_1 - 2)^2 + (x_2 - 1)^2 \\ s.t. \quad & g_1(x) = x_1 - 2x_2 + 1 = 0 \\ & g_2(x) = x_1^2/4 - x_2^2 + 1 \geq 0 \\ & -1.82 \leq x_1 \leq 0.82; -0.41 \leq x_2 \leq 0.92 \end{aligned} \quad (5)$$

test problem2.

$$\begin{aligned} min \;\; & f(x) = 5.3578547x_3^2 + 0.835689x_1x_5 \\ & +37.293239x_1 - 40792.141 \\ s.t. \quad & 0 \leq 85.334407 + 0.0056858x_2x_5 \\ & +0.00026x_1x_4 - 0.0022053x_3x_5 \leq 92 \\ & 90 \leq 80.51249 + 0.0071317x_2x_5 \\ & +0.00029955x_1x_2 - 0.0021813x_3^2 \leq 110 \\ & 20 \leq 9.300961 + 0.0047026x_3x_5 \\ & +0.00012547x_1x_3 - 0.0019085x_3x_4 \leq 25 \\ & 78 \leq x_1 \leq 102;\; 33 \leq x_2 \leq 45; \\ & 27 \leq x_3,\; x_4,\; x_5 \leq 45 \end{aligned} \quad (6)$$

In calculating test-problem1, the penalty function is given by

$$p(x) = \begin{cases} 0, & x \text{ is feasible} \\ \pm fun \times g_{max}, & \text{otherwise} \end{cases} \quad (7)$$

$$g_{max} = max\{|g_i(x)|, |h_j(x)|, i = 1, 2, \cdots, n; \; j = 1, 2, \cdots, m\} \quad (8)$$

Where fun is fitness value of the individual prior to penalty. In simulations, let pop-size=100, maxgen=100, run 10 time at random.

Table 1 The comparison of result on test-problem1

algorithm	$f(x)$	x_1	x_2	$g_1(x)$	$g_2(x)$
HCGA	1.4005	0.8200	0.9100	0	0.0038
Homaifar	1.4339	0.8080	0.8854	0.037	0.0052
Fogel	1.3788	0.8333	0.9124	0.008	−0.006

Table2 The comparison of result on test-problem2

algorithm	$f(x)$	x_1	x_2	x_3	x_4
HCGA	−31023	78.00	33.00	27.09	44.98
Homaifar	−30175	80.61	34.21	31.34	42.05
Fogel	−31006	78.00	33.00	27.14	44.90

algorithm	x_5	$g_1(x)$	$g_2(x)$	$g_3(x)$
HCGA	44.91	91.99	100.40	20.00
Homaifar	34.85	90.58	99.41	20.12
Fogel	44.90	91.98	100.40	20.01

Table 1 presents a comparison of result for this test-problem among HCGA and that of Homaifar(1994) and Fogel(1994).In order to illuminate distinctly, test-problem2 is translated to maximum problem. Table 2 and Figure 1 present a comparison of result on test-problem2.

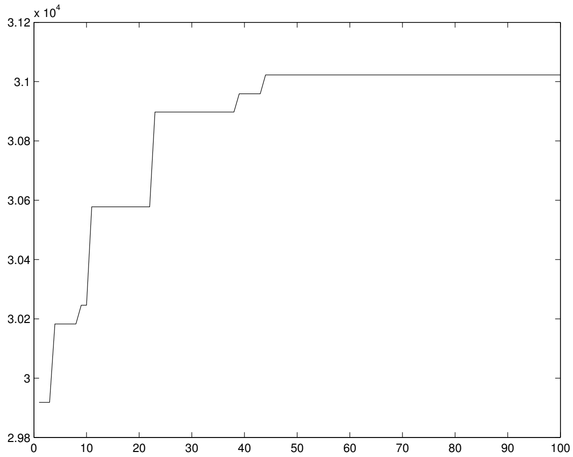

Fig. 1. The actual and predicted outputs at first prediction

Table 1 and table 2 show that HCGA satisfies constraints with high precision and has good accuracy, which exhibits the advantage of hybrid coding and improved mutation operator. The optimum value for test problem in the study by Fogel(1994) is better than the one obtained in this paper. However, the optimum solution gained by Fogel(1994) does not satisfy the constraints and it is not rigorous feasible solution. Figure 1 shows that optimum value is enhanced in a stair-like fashion. This shows that accelerated operator has improved searching performance of algorithm and further verifies the algorithm's feasibility and effectiveness.

5. CONCLUSION

Binary encoding and real encoding are combined to improve the general performance of algorithm. Based on the accelerated searching strategy of traditional direct optimal methods, accelerated operator is introduced into the genetic algorithms to accelerate the convergence speed. Improved variable step of Gaussian mutation is proposed. Thus, global convergence is improved and local searching ability is elevated. The solution gained by the algorithm is much more accurate.

6. ACKNOWLEDGEMENT

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