Simulation Study of Improving Mutative Scale Chaos Optimization Algorithmin Complex Nonlinear System

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Abstract. This paper addresses a reliability optimization problem, where the motive is to select the best optimization method for complex nonlinear system. In order to avoid blind and repeated searching of chaos optimization in searching space of complex nonlinear system, an improving mutative scale chaos optimization algorithm has been proposed to solve the problems. The algorithm counts better value for every searching and sets a sign A in the chaos searching, when the numbers of better value searched is equal to A, the searching space is dynamic reduced according scale, and the above course is repeated in the lesser scale till global optimal value is found. In order to check the reliability of the proposed solution methodology, five complex nonlinear functions have been simulated, the simulation results show that algorithm is simple and local searching ability is better, the efficiency is higher than that of mutative scale chaos optimization, and results demonstrate the benefits of the proposed algorithm for solving this type of problem.

Ⅰ. INTRODUCTION

To seek optimal parameters of control system, a number of exact methods have been proposed so far to deal with the combinatorial optimization problems, such as BP algorithm, gradient descent method, and so on, but they have disadvantages of slow convergence and tend to become trapped in local minimum. Simulate annealing method has been widely applied to various optimization problems too[1], but which requires subtle adjustment of parameters in the annealing schedule such as the size of the temperature steps during annealing, the temperature range, the number of re-starts and re-direction of the search, etc. To design optimal parameters of system in detail is very difficult only by them.

Chaos optimization is an effective method that makes use of chaotic variables for optimal search. Using the features of ergodicity and randomness of chaotic motion does the search process; it can continually search for the optimal solution, and overcome the local minimum problem. Because the chaos search dynamics is confined in a relatively low-dimensional fractal space, compared to the stochastic search, which seems to realize an efficient search for a variety of optimization problems[2]. A chaos optimization algorithm has been proposed by literature [3], the optimal variables are transformed into chaotic variables by method of carrier-wave. It takes advantage of the intrinsic stochastic property and ergodicity of chaos movement to escape from the local minima, and direct optimization search within global range. But when search space is big, its search speed is too slow and effect is not good. A mutative scale chaos optimization method is proposed based on the chaos variables by literature [4], by continually reducing the searching space of variable optimized and enhancing the searching precision, the method made up lake of the literature, but it's step is complex and blind and repeated searching is not been avoided.

An improving mutative scale chaos optimization algorithm is proposed in base of literature[4]. The algorithm counts better value for every searching and sets a sign A in the chaos searching, when the numbers of better value searched is equal to A, the searching space is dynamic reduced

according scale, and the above course is repeated in the lesser scale till global optimal value is found. The method can improve search efficiency and local search ability, and its program is very simple.

II. IMPROVING MUTATIVE SCALE

CHAOS OPTIMIZATION ALGORITHM

On the global minimum optimization problem of continuous object,

$$\min f(x_i)$$
$$x_i \in [a_i, b_i], \quad i = 1, 2, \cdots, n \qquad (1)$$

In this paper optimization search is carried with Logistic mapping chaos variable.

$$x_{n+1} = 4x_n(1 - x_n) \qquad (2)$$

Steps of algorithm are as following:

Step1: Initialization. Giving N a larger circulation number and M a proper circulation number, the optimization variable range is as $[a_i, b_i]$;

Step2: Giving i different stochastically initialization values to $x_{i,1}$ from (0,1), $x_i^* = x_{i,1}$, the initialization $time = 0$ and the initialization value of object function $f^*(x)$ as a larger number, then the better optimizing times are A;

Step3: For $m = 1 : M$ and $n = 1 : N$, mapping $x_{i,n}$ differently to corresponding defining field:

$$x'_{i,n} = a_i + x_{i,n}(b_i - a_i) \qquad (3)$$

Step4: carry $x'_{i,n}$ to needed function and compare with it:

if $f^*(x) = f(x'_{i,n})$,

$x_i^* = x'_{i,n}$, $time = time + 1$,

if $time \geq A$ then go to Step7, otherwise continue.

Step5: carry $x_{i,n}$ to Logistic formula:

$$x''_{i,n} = 4x_{i,n}(1 - x_{i,n})$$

Step6: giving $x_{i,n} = x''_{i,n}$, $n = n + 1$

if $n < N$ then go to Step3, otherwise continue.

Step7: take the above x_i^* as the approximation value of global optimization, and then reduce the optimizing range centered with it.

$$a'_i = x_i^* - (b_i - a_i)/(m + 1) \qquad (4)$$
$$b'_i = x_i^* + (b_i - a_i)/(m + 1) \qquad (5)$$

（notes：If function is symmetrical on some point and all variables' optimizing range is same then reducing searching range centered with x_1^* is a better way.

In order to assure searching ranges not to go beyond boundary make the restriction as followings:

if $a'_i < a_i$, then $a'_i = a_i$,

if $b'_i > b_i$, then $b'_i = b_i$

Step8: $m = m + 1$

if $m < \mathrm{M}$, then give $a_i = a'_i$, $b_i = b'_i$,

return step3 , otherwise continue.

Step9: when the suspending searching condition is meted, the optimization parameter x_i^* is gained from minimum of $f^*(x)$

Ⅲ. EXAMPLES

By way of compare, the five complex testing functions are simulated.

$$F_1 = 100(x_1^2 - x_2)^2 + (1 - x_1)^2 ,$$
$$-2.048 \le x_1, x_2 \le 2.048 \qquad (6)$$

$$F_2 = (4 - 2.1x_1^2 + x_1^4/3)x_1^2 + x_1 x_2 + (-4 + 4x_2^2)x_2^2 ,$$
$$-100 < x_1, x_2 < 100 \qquad (7)$$

$$F_3 = -0.5 + (\sin^2(\sqrt{x_1^2 + x_2^2}) - 0.5)\big/(1 + 0.001(x_1^2 + x_2^2))^2 ,$$
$$-100 < x_1, x_2 < 100 \qquad (8)$$

$$F_4 = (x_1^2 + x_2^2)^{0.25}[\sin^2(50(x_1^2 + x_2^2)^{0.1} + 1],$$
$$-100 < \mathrm{x}_1, \mathrm{x}_2 < 100 \qquad (9)$$

$$F_5 = [1 + (x_1 + x_2 + 1)^2$$
$$(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1 x_2 + 3x_2^2)]$$
$$\cdot [30 + (2x_1 - 3x_2)^2$$
$$(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1 x_2 + 27x_2^2)]$$
$$-2 \le x_1, x_2 \le 2 \qquad (10)$$

According the methods have been used of the literature [3], the literature [4] and this paper, stochastic select initial values in (0, 1) range to simulating, the simulated results are shown in Tab.

TABLE 1 The compare of methods this paper and literature [3, 4]

function	Optimal value	global extremum	optimize time (S)		
			arithmetic of literature [3]	arithmetic of literature [4]	arithmetic of this paper
F_1	(1. 1.)	0	0.9257	0.8574	0.3600
F_2	(-0.089, 0.712) (0.089, -0.712)	-1.031	8.3562	0.7774	0.6210
F_3	(0, 0)	-1	52.793	6.6849	1.6820
F_4	(0, 0)	0	225.5385	22.3115	3.3050
F_5	(0,-1)	3	15.6388	3.9731	1.6420

As discussed in the above table 1 shows that the optimize time of this paper is little compare with that of literature [3] and [4] in time.

Ⅳ. SIMULATION STUDY

Simulate to the above five complex test functions in each variable range [a_i, b_i], the results are shown in Fig.1 ~ Fig.5. Abscissa is time of search, "*"is value has been searched, as F_1、F_2 and F_5 are too convergence in the figure, only local function values are lined out.
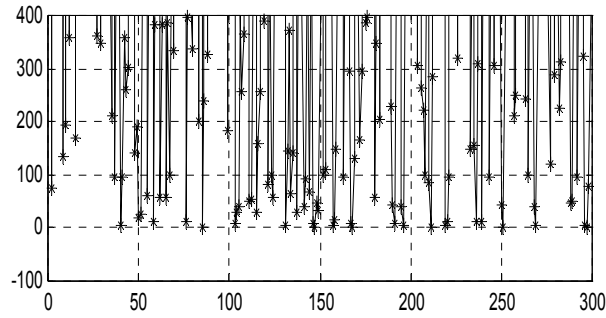

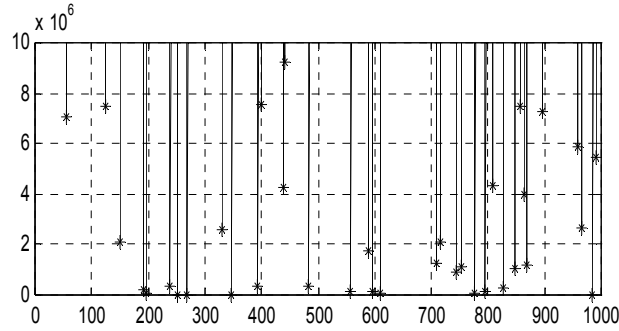Fig.1　Portrait local function value of F_1 at chaos search 300 time

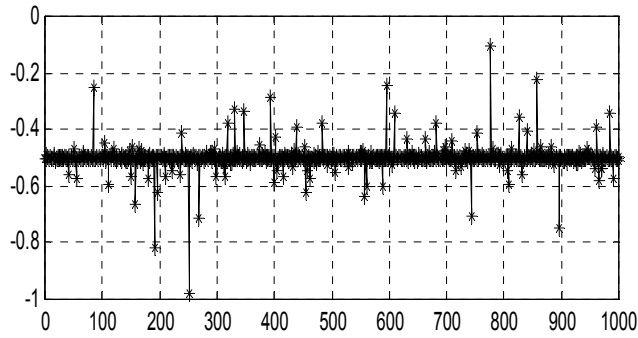Fig.2　Portrait local function value of F_2 at chaos search 1000 time

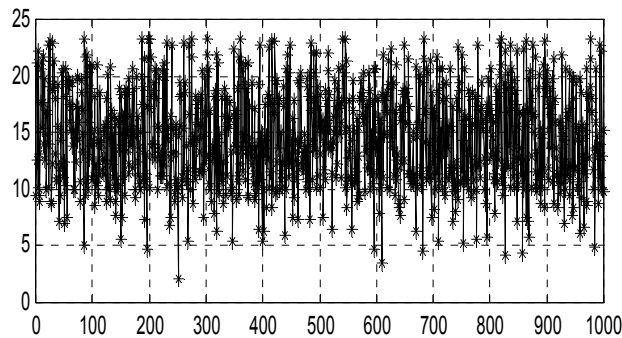Fig.3 Chaos search function value of F_3

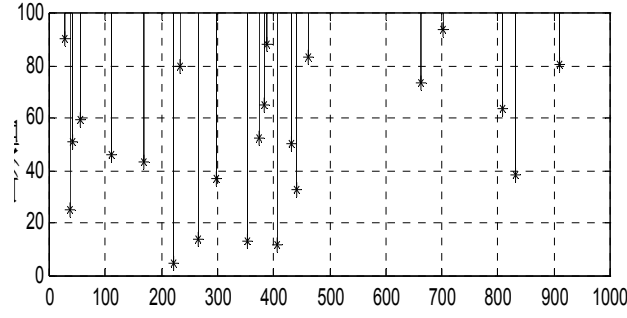Fig.4　Chaos search function value of F_4

Fig.5　Portrait local function value of F_5 at chaos search 1000 time

Seeing from Figure, currently optimal value is discovered of small range function F_1 and F_5 in compare to three times, currently optimal value is discovered of big range function F_2 and F_4 in compare to five and six times, and that is discovered of complex function F_3 in compare to seven times. My experience is that N is equal to 1000, A is equal to $5 \sim 7$, M is equal to $20 \sim 30$ when search space is big, and A is equal to $3 \sim 5$, M is equal to $10 \sim 20$ when search space is small.

V. ASTRINGENCY　PROOF

Definition 1 Suppose $x_n, n \in (1,2,\cdots,N)$ are chaos sequence is defined in chaos dynamic system, if chaos variable x exist, and $\forall \varepsilon > 0$, as while as

$$\lim_{n \to \infty} P(|x_n - x| < \varepsilon) = 1$$

Then chaos sequence $\{x_n\}$ is convergent to chaos variable x according to probability.

Definition 2 On above chaos sequence x_n and chaos variable x,

If 　　$P\{\lim_{n \to \infty}(x_n - x) = 0\} = 1$

or if $\forall \varepsilon > 0$, as will as

$$P\{\bigcap_{n=1}^{\infty} \bigcup_{i \geq n}(|x_i - x| \geq \varepsilon)\} = 0$$

Then chaos sequence $\{x_n\}$ can be convergent to chaos variable x according to probability 1. According to definition 1 and 2, we can gained theorem is shown as fellows.

Theorem Giving sequence produced by function $f(x)$ with chaos algorithm as $\{x_n\}$ then $\min f(x)$ can be convergent to global optimal value x^* based on probability 1.

Prove suppose $x_i^* = \arg \min_{x \in N} f(x)$, $N \in R^n$

Giving ε 's small range of global optimal value x^* as N_ε, then for any positive ε, $\delta > 0$ exists and meets the following:

$$N_\varepsilon = \{x \big| |x - x^*| < \delta, \ |f(x) - f(x^*)| < \varepsilon\}, \quad x \in R^i$$

The random sequence embedded in N_ε is as followings:

$$A_k = \{x | x_{i,n}^* \in N_\varepsilon, n \in \{1,2,\cdots,N\}\}$$

It stands for iterative sequence going into x^* 's near field N_ε nth. Because chaos optimization algorithm is a descend algorithm mechanism, $f(x_{i,n})$ is a monotony descend sequence by all appearances. So exists:

$$f(x_{i,1}) > f(x_{i,2}) > \cdots > f(x_{i,n}) > \cdots > f(x^*)$$

It makes out that x_ε is a searching field. Accordingly as long as the parameter $x_{i,i}$ goes into x_τ the parameter $x_{i,i+1}$ goes into x_ε certainly. Namely when event A_1 occurs event A_2 occurs certainly, it causes occurring of event A_3 certainly, …, so exists:

$$A_1 \subset A_2 \subset \cdots \subset A_n \subset \cdots \quad \cdots$$

It also accounts for probability being monotony ascend.

$$P(A_1) \le P(A_2) \le \cdots \le P(A_n) \le \cdots$$

And $0 \le P(A_n) \le 1$, Based on the principle that monotony ascends series with upper boundary is of limit certainly, random accident series $A_n \ (n=1,2\cdots)$ is convergent on probability:

$$\lim_{n\to\infty} P(A_n) = 1$$

VI. CONCLUSIONS

According to above discussions and studies, the optimization algorithm expatiated in this paper has remedied the shortage of paper [4]. Not only has the chaos optimizing process avoided overlap searching but can dynamically reduce searching space according process .This algorithm can over the local minimum and enhance local searching ability. It has the feature of global optimization and the simple algorithm's construct .The algorithm is easy to realize and of high searching efficiency.

Acknowledgment

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