TELKOMNIKA, Vol.11, No.2, February 2013, pp. 975~984
ISSN: 2302-4046

Chaotic Immune Genetic Hybrid Algorithms and Its Application

Weijian Ren*, Chaohai Kang ,Yingying Li, Liying Gong
School of Electrical and Information Engineering,
Northeast Petroleum University, HeiLongJiang DaQing 163318, China
*Corresponding author, e-mail:renwj@126.com

Abstract

To solve the shortage in genetic algorithms, such as slow convergence speed, poor local searching capability and easy prematurity, firstly, the immune memory recognition function was introduced, to speed up the searching speed and improve the overall searching capabilities of genetic algorithm. Secondly, the Hénon chaotic map was introduced into the generation of the initial population, made the generated initial population uniformly distributed in the solution space, to reduce data redundancy, increase the diversity of antibody population and the search range of initial population manipulation, prevent the defect of falling into local optimum. Finally, Logistic map was introduced into manipulation of crossover and mutation, meanwhile the map was used to produce the chaotic disturbance strategy on the memory and populations antibodies , to improve the quality of optimal solution and the searching speed of the algorithm, increase efficient of searching. It was proved that the above hybrid algorithm is convergence by mathematics method. The results of function optimization show that the above hybrid algorithm is valid and has better performance than other algorithms.

Keywords: *genetic algorithms, immune algorithm, chaotic, function optimization*

1. Introduction

In recent decades, the examples to optimize the functions in theory or practical application can be seen everywhere. There are some fixed forms of mathematical modeling, which can be obtained from many engineering problems through the corresponding conversion. That is, the practical problems in engineering can be solved by converting them into the optimization problems of mathematical model. There are a wide range of problems in real life, but these complex functions formed by a variety of complex issues, which can not be solved by a general optimization algorithm usually. Now, there is not a better optimization algorithm to optimize the kinds of complex functions. In recent years, the algorithms of genetic algorithm and immune algorithm are studied much. The genetic algorithm, a biological intelligent evolutionary algorithm, is mainly drawn from the natural selection mechanism of biological, there are many advantages in it, for example ,the capability of good global searching and being easy implemented, but there are some problems, for example , poor local searching capability, slow convergence speed, and easy prematurely [1]. The immune genetic algorithm [2] is a intelligence evolutionary algorithm combining with the biological, and this algorithm is derived from the manipulation mechanism of human and other higher animals'. Based on the theory of genetic algorithm, the immune mechanism is introduced into, and this is the primary improvement of immune genetic algorithm. Simultaneously, it also can be considered as a new intelligence evolutionary algorithm mixing with the biological. The population diversity can be better maintained and phenomena of premature convergence and oscillation can be reduced with the immune genetic algorithm, too, but the immune genetic algorithm still has three main shortcomings, respectively, falling into local optimal, a long computation time and a slow searching speed near the optimal solution. Since Hénon chaotic map [3] has some excellent characteristics, such as randomness, ergodicity and the sensitivity of initial value, these make the generated initial population uniformly distributed in the solution space, simultaneously, the quality of evolution is improved and the defect of data redundancy is reduced also. Consequently, there will be a better prospect by compensating the defects of immune genetic algorithm with the series features of chaotic theory [4].

Received September 21, 2012; Revised January 3, 2012; Accepted January 15, 2013

In order to solve the main problems of genetic algorithms, slow convergence speed, poor local searching capability and easy prematurity, in this paper, Hybrid thinking [5] is introduced from elsewhere. The chaotic immune genetic which is a new intelligent algorithm, is formed by chaotic combining with immune mechanism. In this paper, the proposed algorithm is contrasted with genetic algorithm and immune genetic algorithm. At last, the global search capability, convergence performance and the speed of searching the optimal solution are all tested by the simulation results, meanwhile a comparative analysis is made above the results.

2. The Description Of Function Optimization Problem

The function optimization problem [6] is mainly used to solve a more complex function optimization. The nature of function optimization is finding the optimal solution of the objective function by iteration. In general, the target is searched by optimizing the “function” of the objective function. The described characteristics of function usually include the continuity, discrete, linear, non linear and punch. The solution of function optimization problem which has constraint conditions can be always made to remain viable by taking advantage of specialized operator, or it can be transformed into an unconstrained problem by using the way of penalty function. Therefore, the main researches are focused on optimizing the function with unconstrained conditions. General function optimization problem can be described as the following form [7]:

$$\max f(x_i)\begin{cases} f(x_i)\in R^n \\ x_i \in S \end{cases} \text{ or } \min f(x_i)\begin{cases} f(x_i)\in R^n \\ x_i \in S \end{cases} \tag{1}$$

where $f(x_i)$ is the objective function; x_i is the domain of the function; R^n is the range of the objective function; S is the variable of objective function. The problem described in equation (1) is the maximum or minimum value of the target function. Usually the maximum and minimum problems can be transformed into each other, that is, the maximum problem of the target function $f(x_i)$ can become the minimum one through negation, and the converse is also true.

3. Chaotic Immune Genetic Algorithm

3.1.The generation of the initial population

The initial population of antibodies is generated by the use of Hénon chaotic map in this paper, and the specific description of the process is described as follows:

(1) The unit matrix $E_{m\times m}$ is generated at first;

(2) Set $a=1.5$, $b=0.4$, $x_0 = rand(1)$ ($rand(1)$ is a random number between $[0,1]$, $y_0 = 0$) ;

(3) The outer loop is entered; the number of cycles is the sum of the individuals' number of population and memory;

(4) The inner loop is re-entered. $2*m$ is the defined number of cycles;

(5) The two chaotic space y_1, y_2 as defined are generated by the Hénon chaotic map, at the same time, y_1, y_2 will be converted to the internal of space $[0,1]$, and then they will be mapped to the space $[1,m]$, thus the corresponding i, j value can be obtained;

(6)The size of value i, j is judged, if $i = j$, the chaotic optimal manipulation needn't to be conducted, and chaotic exchanging and chaotic shifting need to be conducted on chaotic optimization manipulation there, if $i \neq j$, the chaotic optimal manipulation need to be conducted, and the chaotic exchanging manipulation is that the positions of column value i and column value j in matrix should be exchanged during, and the chaotic shifting manipulation is that the column i is moved out from the matrix first, then the column i extracted will be placed on the position of column j ,and thus each column after $i+1$ is moved forward with one column in turn;

(7) Judging whether the number of inner loop is reached, if the number of inner loop is not reached, the requisite number of times will be continue completed, and if the number of inner loop is reached, the next step will be started;

(8) Judging whether the number of outer loop is reached, if the number of outer loop is not reached the requisite number of times will be continue completed, and if the number of outer loop is reached, the next step will be started;

(9) At last, the individuals in groups and memory, which contain the one only represented by $0,1$, are converted into a corresponding array of decimal and returned.

3.2.Carrying on the Chaotic optimization for the individual of outstanding population and memory

The chaotic disturbance on the outstanding individuals is completed by Logistic chaotic map in this algorithm, and the main steps are as the follows:

(1) Firstly, individuals optimized in a population are converted into $0,1$ phalanx;

(2)The two sets of numerical sequence, respectively n_1, n_2, are generated by Logistic chaotic map, the initial value of Logistic chaotic map is a random value in the space $[0,1]$, then it will be transformed into the space $[1,m]$ and the values i, j will be calculated;

(3) Judging whether the manipulation of chaotic optimization should be carried out.

A threshold factor h is defined before is the judgment made, and the comparison manipulation will be made to judge if the original affinity of individuals in a transformed population is greater than the antibody affinity of original populations, if the changing conditions is met, the individuals in original population will be replaced by the one in new population, and if not, the replace manipulation need not to be done.

3.3.The inhibition and promotion of antibody in the generation process

If the phenomenon of affinity occurs when the antibody meeting the antigen, it is believe that that antibody is relatively close to the optimal solution, otherwise, it is believe that that antibody is away from the optimal solution. If some of the antibodies are found being in higher concentrations relatively in the chromosome group during the optimization process, some stagnation may be leaded in the optimization process, and the premature convergence phenomena of algorithm may be caused eventually. In order to prevent the above problems from taking place, the way of concentration control will be used to controlling the population size of same or similar antibody.

The variable C_i is used to represent the antibody concentration, which refers to the ratio of similar antibodies accounted for the entire antibody in the whole group, C_i is calculated as the formula (2) below:

$$C_i = \frac{\text{the number of antibodies which the similarity with the antibody is larger than } \lambda}{\text{N}} \tag{2}$$

where λ is the similarity constant, and its range is generally $0.95 < \lambda < 1$.

The antibody concentration is calculated by using the equation (2).At the same time, the antibody concentration which is greater than a certain value will be found out in all antibody, and they each are recorded as individual $1,2,3,..,t$ respectively, and the method of calculating the concentration probability $\boldsymbol{P_d}$ of individuals with a specific number is defined as the formula (3) shown:

$$P_d = \frac{1}{N}\left(1 - \frac{t}{N}\right) \tag{3}$$

The method of calculating the probability of other $N-t$ antibody in the groups is defined as the formula (4) shown:

$$P_d = \frac{1}{N}\left(1 + \frac{t^2}{N^2 - N*t}\right) \tag{4}$$

The affinity probability P_f of single antibody is calculated by using the roulette wheel selection method. The selection probability P of each antibody is composed with two parts, they are the affinity probability P_f and concentration probability P_d respectively, and the expression can be obtained as the formula (5) shown:

$$P = \alpha P_f + (1-\alpha) P_d \tag{5}$$

The affinity coefficients is represented with α in the formula (5), where $\alpha > 0$, $P_f < 1$ and $P_d < 1$. It can be seen from the formula (5) that the choice probability of antibody is determined both by the affinity probability P_f and the concentration probability P_d , the selection probability will become greater when the value of antibody affinity P_f become greater, and the selection probability must be also smaller when the value of antibody affinity P_d become greater. The high antibody affinity can be retained by such choice way, which can be seen from the calculation, and the performance of antibody diversity can be improved also, the occurrence of falling into the premature convergence will be prevented eventually.

The selection of affinity coefficient value α must be paid attention to when selecting the coefficient of parameter, if the value is too small, the role played by the affinity choice mechanism will be reduced in the genetic algorithm, and this is not conducive to the evolution manipulation, and if the value is too large, the ability of self-regulation mechanisms will be reduced in the immune genetic algorithm, and the diversity of antibodies is likely to be destroyed in the population, the phenomena of premature and convergence may also be caused.

3.4.Chaotic crossover and chaotic mutation manipulation in genetic manipulation

In this paper, the following manipulations will be performed on the basic genetic algorithm, crossover operator in genetic algorithm is replaced with chaotic crossover, and mutation operator in the genetic algorithm is replaced with chaotic mutation, the rest of the manipulation is similar with the basic genetic algorithm. The crossover and mutation operator in the genetic manipulations can be changed by using the chaotic control strategy, and the crossover and mutation manipulations of a strong random in determining the probability can be replaced. So the "blindness" of the random manipulation in genetic algorithm can be well avoided. Thus the diversity of population individuals can be ensured, and the problem of falling into local optimum value can be prevented.

The four chaotic sequences defined separately as $x_{k1}, x_{k2}, x_{k3}, x_{k4}$ will be introduced during the genetic manipulation process, the characteristics that haphazard and random distribution of chaotic sequence, which is a performance in a relatively short period of time, but all state properties can be traversed without replication by complete chaotic sequence during the interval $[0,1]$ are used. The individual diversity of population showing in the short term can be helped greatly with the random characteristic in such a short period of time, so the falling into local optimum can be avoided. The other hand, the advantage of chaotic ergodicity can be made use of, so the repetition and blind manipulation, which result of the random manipulation of chaotic manipulation in a short period, can be prevented by this advantage, thus the diversity of populations can be protected, the occurrence of premature phenomenon can be prevented, and the reduction of the searching speed due to the repeat searching can be also prevented.

The specific steps of chaotic crossover and chaotic mutation are as follows:

(1) The chaotic crossover operator:

The crossover interval is defined as $c_m \in [0,1]$, the question that whether the chaotic sequence x_{k1} is in the crossover-range c_m is judged at first, at the same time, the question that whether the two pair individuals in a population are carried on crossover manipulation is judged too, if the chaotic sequence x_{k1} is in the interval c_m , the crossover manipulation need to be carried on, otherwise, the crossover manipulation needn't to be.

Before the chaotic crossover manipulation, the range $[0,1]$ is divided into equal number of intervals based on the gene fragment number in the chromosome, and each subinterval is marked with number, the location of gene fragment in chaotic crossover operator can be determined by the number of interval x_{k2} , the crossover manipulation is carried out with each other corresponding gene fragment of chromosome pairing when the position of crossover manipulation has been determined, so a new sub-chromosome is generated.

(2) The chaotic mutation manipulation

The variation interval is defined as $c_v \in [0,1]$, the question that whether the chaotic sequence x_{k3} is in the variation interval c_v is judged at first, at the same time, the question that whether the two pair individuals in a population are carried out mutation manipulation is judged too, if the chaotic sequence x_{k3} in the interval c_v, the mutation manipulation need to be carried out, otherwise, the mutation manipulation needn't to be.

Before the chaotic mutation manipulation, the range $[0,1]$ is divided into equal number of intervals based on the gene fragment number in the chromosome, and each subinterval is marked with number, the location of gene fragments in chaotic mutation manipulation can be determined by the number of interval x_{k4}, the mutation manipulation is carried out with each other corresponding gene fragment of chromosome pairing when the position of mutation manipulation has been determined, so a new sub-chromosome is generated.

3.5. The chaotic disturbance manipulation for population antibodies

The chaotic disturbance for the antibody is completed by choosing the method of Logistic chaotic map, the specific method is the same manipulation as chaotic disturbance for individuals in excellent population and memory, the purpose is that only the antibody, which has the high superiority of original antibody, can be entered the next cycle with the achieved conditions, thus the state of falling into the local optimal solution can be avoided.

4. Proving of the Algorithm Convergence

The global searching capability and precision of the immune genetic optimization algorithm and genetic chaotic optimization algorithm are all better than a single genetic algorithm, at the same time, the calculation efficiency of a single genetic algorithm can be improved by the two improvements of the genetic algorithm presented in this paper, the practicality of the algorithm is increased, and the convergence performance of the combination algorithm can also be guaranteed.

The immune genetic algorithm combined with immune algorithm will be converged to global optimal solution with probability1. In the paper, the improvement for the basic genetic algorithm, which is the immune genetic algorithm based on chaotic, can be seen as the introduction of chaotic theory on the basis of the immune genetic algorithm, the defects of standard genetic algorithm can be avoided in theory, thus the quality of optimal solution is improved.

Theorem 1 the immune genetic algorithm is converged to the global optimal solution with probability 1 based on chaotic. Prove that, set the equation $x^* = \arg\min f(x)$, the sequence $\{x_1^k\}$ is a sequence of solutions that generated by the immune genetic algorithm combined by the genetic algorithm and immune algorithm, The sequence $\{x_2^k\}$ is a sequence of solutions that generated by the immune genetic algorithm based on the chaotic theory. When the variable $i \le j$, the inequalities $f(x_1^i) \ge f(x_1^j)$ and $f(x_2^i) \ge f(x_2^j)$ can be deduced. The inequality $f(x_1^k) \ge f(x_2^k)$ can be drawn according to the nature of the recursive algorithm, and the sequence $\{f(x_1^k)\}$ drawn in front is a convergent sequence, the formula $\lim_{k\to\infty} P\{f(x_1^k) = f(x^*)\} = 1$ can be drawn according to the clipping theorem's features of convergent sequence, because the inequality $f(x_1^k) \ge f(x_2^k) \ge f(x^*)$ exists, the known sequence $\{f(x_1^k)\}$ is as a convergent sequence, so the conclusion that the sequence $\{f(x_2^k)\}$ is also a convergent sequence can be drawn, and $\lim_{k\to\infty} P\{f(x_2^k) = f(x^*)\} = 1$.

So the correctness of this theorem that the chaotic theory is introduced into the immune genetic algorithm can be proved, the immune genetic algorithm is converged with probability 1 based on chaotic theory in this paper according to of the above proving process.

5. Solving The Problems Of Function Optimization

The chaotic immune genetic algorithm presented in this paper is compared with two selected algorithms by the simulation results.

(1) The Genetic Algorithm [8]:

The operator is selected by using the rotary selection operator in selection manipulation of genetic algorithm, the conventional single-point crossover is used in the crossover manipulation, and the mutation manipulation occurs only when the two individuals are too similar, where the crossover probability is 0.6 and the mutation probability is 0.05;

(2) The Immune Genetic Algorithm [9]:

The same ordinary crossover manipulation and common mutation manipulation are used in the immune genetic algorithm, where the crossover probability is 0.6 and the mutation probability is 0.05.

In order to prove the validity of the immune genetic algorithm proposed in the paper based on chaotic theory, six typical test functions are selected respectively, the standard genetic algorithm, immune genetic algorithm and chaotic immune genetic algorithm proposed in this paper are used in the test, the performance of each one are compared with the others.

The memory size is defined as 40 in the chaotic immune genetic algorithm proposed in this paper, the population size is defined as 100, and the maximum number of iterations is defined as 100, the decimal encoding is used by the individual of population antibody generated by Hénon chaotic map, the affinity between antibodies can be expressed by the concentration of population individuals. The special attention should be paid to the selection of the threshold factor in the chaotic optimization, if the selected h is too large, some better solutions because of not getting transform will not be continue transformed towards the direction of the optimal solution, if the selected h is too small, a part of better solutions will be transformed towards the direction of poor solution, thus the global optimal solution can not be obtained, here $h = 1.5$ is obtained by the experience [10].

The test charts and test results obtained in this paper are as follows.

5.1.Test function

Function1: $f_1 = 100 - (x^2 - y)^2 - (1-x)^2$ where $[x, y] \in [-2, 2]$

The global maximum value 100 of function 1 is obtained at $[1,1]$, and there are countless value close to the optimal value around $[1,1]$, so it belong to a function of very easy falling into local optimal; the extreme value distribution of function shown in Figure 1.

Function2: $f_2 = 30 - x^2 + 10\cos(2\pi x) - y^2 + 10\cos(2\pi y)$ where $[x, y] \in [-1.5, 1.5]$

Function2 is a function belongs to multivariate and multi-peaks, the global maximum 50 is obtained at $[0,0]$, and eight local optimum value exist around the origin $[0,0]$, so it belong to a function of very easy falling into local optimal; the extreme value distribution of function shown in Figure 2:

Function 3: $f_3 = 6 - (x^2 + y^2)^{0.25} * \{\sin[50(x^2 + y^2)^{0.1}]^2 + 1\}$ where $[x, y] \in [-0.05, 0.05]$

The global maximum value 6 of function 3 is obtained at $[0,0]$, and there are infinitely local optimums around the origin $[0,0]$, so it belong to a function of very easy falling into local optimal; the extreme value distribution of function shown in Figure 3:

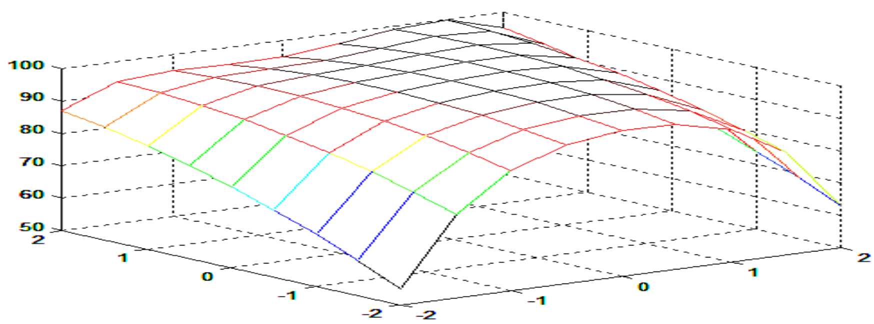

Figure1. The Image of Function1

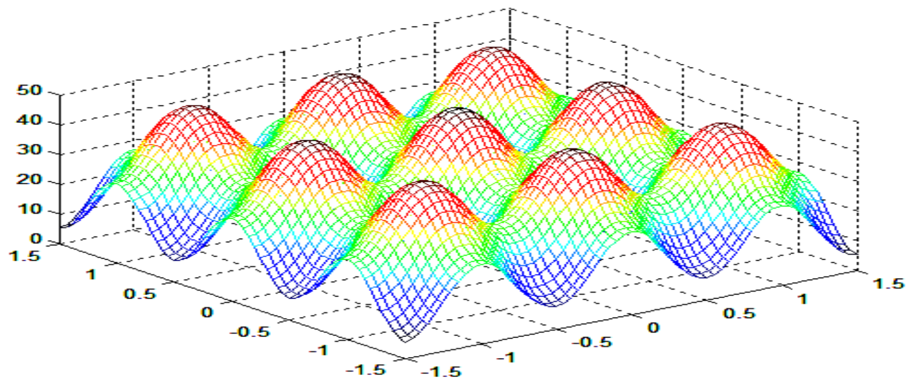

Figure2. The Image of Function2

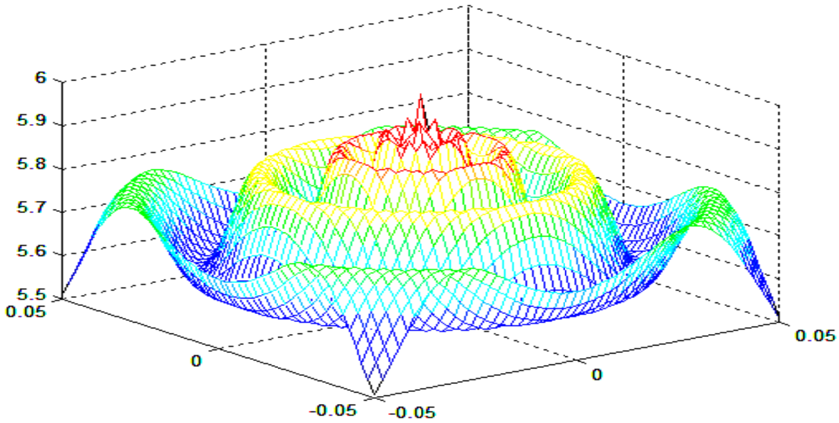

Figure3. The Image of Function3

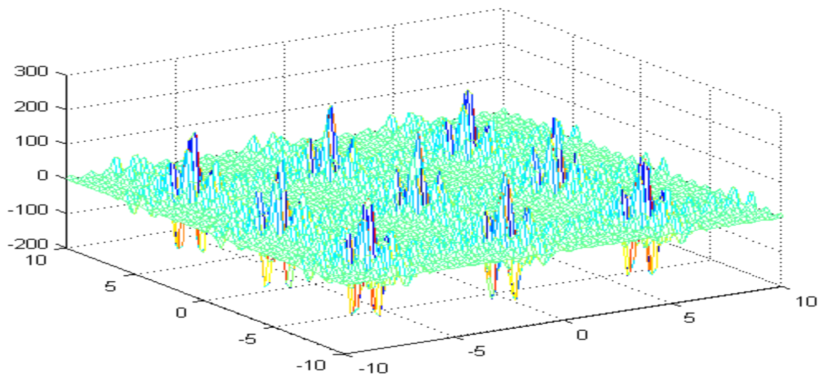

Figure4. The Image of Function 4

Function 4: The Schaffer6 Function $f_6(x,y) = 0.5 - \frac{\sin^2\sqrt{x^2+y^2} - 0.5}{(1+0.001(x^2+y^2))^2}$ where $-50 \le x, y \le 50$

The maximum value 1 of function 6 is obtained at $[0,0]$, there are infinitely local optimums around the origin $[0,0]$; the extreme value distribution of Schaffer6 function shown in Figure 4:

5.2.Test result

There are many uncertainties in the results of single run, in order to avoid the impact from the experimental result. Each optimized function, the two algorithms compared with the proposed algorithms and the proposed algorithms in this paper, is run for 100 times. The absolute value of the most advantage value[x,y], which is solved by the function:

$f_1 = 100 - (x^2 - y)^2 - (1 - x)^2$, and the function $f_2 = 30 - x^2 + 10\cos(2\pi x) - y^2 + 10\cos(2\pi y)$,

and a given optimal deviation value should be less than 10-3;The absolute value of the most advantage value, which is solved by the function: $f_3 = 6 - (x^2 + y^2)^{0.25} * \{\sin[50(x^2 + y^2)^{0.1}]^2 + 1\}$,

and a given optimal deviation value should be less than 10-2. If the most advantage value[x,y] can not be less than the minimum deviation of accuracy of it and the optimal value by using a certain algorithm when the required termination generation $T = 100$ is achieved. The conclusion can be judged that the optimizing manipulation for the function fails by using this algorithm. The performance indicators selected in this paper are the convergence times, the average evolution generation of the optimal solution being found, the average convergence time of searching the optimal solution, and the average value of satisfactory solution. The more convergence times can be seen as the higher probability of the optimal solution to be found, and the global optimal solution can be better searched by the algorithm; The more small average evolution generation show that the more fast speed for the optimal solution to be found, the more close between average convergence value, and the given optimal solution show that the higher accuracy of a satisfactory solution being solved by the algorithm.

With the above mentioned limitations, three algorithms, which are all run for 100 times, of genetic, immune genetic, and chaotic immune genetic are compared. The number of satisfactory solution can be found by this manipulation, evolution generation, convergence time and the average of optimal solution being solved during the 100 times running are shown in Table 1-4.

Table 1. The Performance Comparison Of Optimizing Function1

Algorith-ms	The number of convergece	The generation-n of average evolution	The time of average convergen-ce	The value of average convergen-ce
Genetic	41	62.2	1.02s	100
ImmuneGenetic	49	59.3	0.81s	100
Chaotic Immune Genetic	92	51.2	0.74s	100

Table 2. The Performance Comparison Of Optimizing Function2

Algorith-ms	The number of convergece	The generation-n of average evolution	The time of average convergen-ce	The value of average convergen-ce
Genetic	25	100	1.63s	4.9999
ImmuneGenetic	37	89.2	1.41s	50
Chaotic Immune Genetic	87	53.4	1.37s	50

Table 3. The Performance Comparison Of Optimizing Function3

Algorith-ms	The number of convergece	The generation-n of average evolution	The time of average convergen-ce	The value of average convergen-ce
Genetic	21	100	2.20s	5.9851
ImmuneGenetic	42	83.5	1.94s	5.9875
Chaotic Immune Genetic	91	63.3	1.78s	5.9907

Table 4. The Performance Comparison Of Optimizing Function4

Algorith-ms	The number of convergece	The generation-n of average evolution	The time of average convergen-ce	The value of average convergen-ce
Genetic	78	25.6	0.374s	0.9994
ImmuneGenetic	93	21.3	0.138s	0.9998
Chaotic Immune Genetic	98	8.2	0.099s	1

It can be seen from the running results of Table 1-6 that the convergence rate of the chaotic immune genetic algorithm proposed in this paper has a wide range of improvement compared to immune genetic algorithm and standard genetic algorithm under the same basic conditions. Thus the immune genetic algorithm has a stronger capability of global searching, so the problem of falling into local optimum solution can be prevented, and its performance is more sTable. It also can be seen from the Table that the average evolution generation of chaotic immune genetic algorithm, which is compared with immune genetic algorithm and the standard genetic algorithm, is significantly less under the convergence case, the premature convergence can be better avoided by the immune genetic algorithm based on chaotic theory proposed in this paper, at the same time, the global optimal solution can be also found quickly.

The concept of population performance dispersion and population geographical dispersion are introduced respectively, in order to make the performance of the algorithm proposed in this paper observed easily.

Definition 1, the dispersion of population performance is defined as follows:

$D\left(f(x_1),f(x_2),\cdots,f(x_n)\right)$

That is the variance of the individual performance of in the population: $p=\{x_1,x_2\ldots,x_n\}$

Definition 2, the dispersion of population geographical is defined as follows:

$E\left(\|x_1\text{-}c\|,\|x_2\text{-}c\|,\cdots,\|x_n\text{-n}\|\right)$ where $c=E\left(x_1,x_2,\cdots,x_n\right)$ is the center of population gravity, the Euclidean distance is defined as $\|*\|$.

The degree distribution of the population diversity can be expressed by population performance dispersion and population geographical dispersion, the dispersion values of population will be different by using the different algorithms to calculate. If the dispersion value calculated by an algorithm is greater than the one that calculated by another algorithm, it means that the performance of algorithm with larger value of the dispersion calculated is better, namely the diversity of the population is better when using the algorithm and the loss of genetic types can be well avoided.

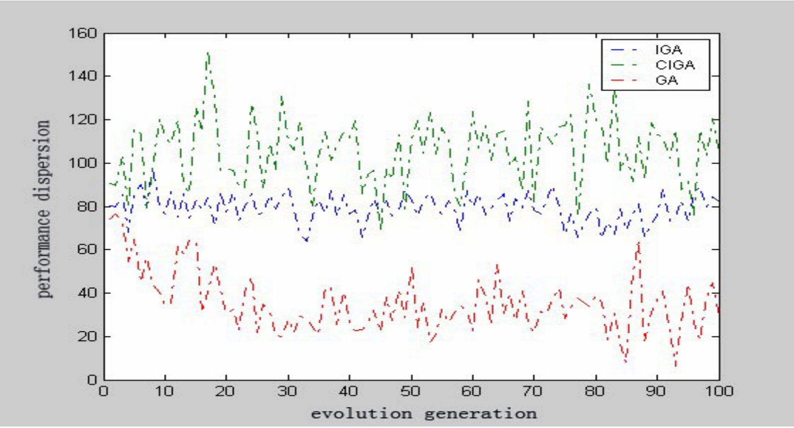

Figure5.the contrast of population performance dispersion by the optimization function 2

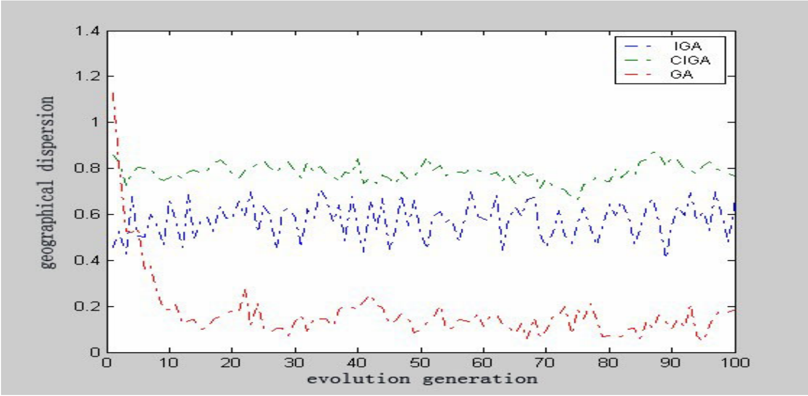

Figure6. the contrast of population geographical dispersion by the optimization function 2

The change curve of population performance dispersion and population geographical dispersion when optimizing the function $f_2 = 30 - x^2 + 10\cos(2\pi x) - y^2 + 10\cos(2\pi y)$ by using the genetic algorithm, immune genetic algorithm and chaotic immune genetic algorithm are shown on the Figure 5 and Figure 6(The chaotic immune genetic algorithm proposed in this paper is shown with the green line, the immune genetic algorithm is shown with the blue line, and the genetic algorithm is shown with the red line),

The conclusions can be drawn from the test results of population dispersion and geographical dispersion shown on the Figure 5 and Figure 6, which using the three algorithms to optimize the function 2 , the performance dispersion as well as the geographical dispersion can be maintained a larger value better by using the immune genetic algorithm, thus the loss of genetic types can be better avoided, the population diversity is maintained, and the probability of global optimum searching is greatly improved.

6.Conclusion

The algorithm of chaotic immune genetic is proposed mainly in this paper. Moreover, the algorithm is used in the optimization of complex functions. The simulation results, which are compared with the genetic algorithm, immune genetic algorithm, demonstrate that the global search ability and convergence performance of the algorithm can be improved. Simultaneously, the speed for searching the optimal solution has been improved significantly also.

References

[1] Sawan Sen, Priyanka Roy, Abhijit Chakravarti, Samarjit Sengupta. Genetator Contribution Based Congestion Management using Multiobjective Genetic Algorithm. *TELKOMNIKA*. 2011; 9(1): 1-8.
[2] Lei Wang, Jin Pan. The Immune Algorithm. *Journal of Electronics*. 2000; 28(7): 74-78.
[3] Cuk Supriyadi Ali Nandar. Parameter Optimization of Pitch Controller for Robust Frequency Control in an Isolated Wind-diesel Hybrid Power System Using Genetic Algorithm. *TELKOMNIKA*. 2008; 6(3): 145-154.
[4] Wang Sunan, Zilong Guo. A Novel Chaos Immune Optimization Combination Algorithm. *Journal of Control and Decision*. 2006; 21(2): 110-114.
[5] Mei Bai. The Summary of Intelligent Control Theory. *Journal of North China Institute of Water Conservancy and Hydroelectric Power*. 2002; 10(1): 330-334.
[6] Dajiang Wang, Ruiying Cai, Xinwei Xu. The Algorithm of Swarm Intelligence and its Application. *Journal of Computer Knowledge and Technology*. 2010; 6(21): 5845-5846.
[7] Ning Xu, Chunguang Li, Jian Zhang, Juebang Yu. The Comparative Study of Several Modern Optimization Algorithms. *Journal of Systems engineering and Electronics*. 2002; 24(12): 100-103.
[8] Xiaohui Yuan, Yanbin Yuan, Sheng Wang. A Novel Adaptive Chaotic Genetic Algorithm. *Journal of Electronic*. 2006; 34(4): 708-712.
[9] He Liu, Meng Huang, Dao Huang. The Research Progress on Optimization Method Based on Chaos Search. *Journal of The Technology of Nanjing University.* 2005; 29(2): 124-128.
[10] Xiao Zhou, Yihua Hu. Chaos Genetic Algorithm and its Application in Function Optimization. *Journal of Computer and Digital Engineering*. 2005; 33: 68-70.