A New Immune Algorithm and Its Application

GUO MENG, CHEN QIUHONG Department of Computer Science and Technology HENAN University of Urban Construction, PingDingShan,Henan Province, 467044, P.R.China Ando1203@163.com

Abstract: - The traditional single clonal selection algorithm has a lot of disadvantages, for example, it is easy to be trapped into local optima, and it has a lot of massive redudacy iteration in its later period and inferior global search ability and so on. In this paper, a new artificial immune algorithm is proposed based on the clonal selection theory and the structure of anti-idiotype(IAAI), which is improved as follows: firstly, IAAI constructs a dynamic clonal expansion, secondly clonal mutation, thirdly dislocated line clonal recombinant, lastly clonal selection. Through the above mentioned several key steps, IAAI is improved in order to achieve the evolution of the whole antibody population, then the new algorithm can have strong search capabilities which make it reach better performance by perfoming global search and local search in many directions in the solution space. Then the global convergence of the new algorithm is analyzed from the test of several typical complex functions. The result shows that the algorithm can effectively overcome the premature problem, and improve the ability of global optimization, the speed of convergence.

Key-Words: - immune algorithm, clonal selection, dynamic clonal expansion, clonal mutation, dynamic adjustment, anti-idiotype

1 Introduction

To solve the optimization problems have became a very important research area which attracted the attention of lots of scholars from the 20th century. At the same time, the mathematical questions are modeling which is related to the real world problems in order to get mathematical functions. However, these functions are very complex, and they have non-linear and multi-dimensional feature. So the general algorithm can not be used to solve above functions effectively, and then solutions to these problems will necessitate additional new algorithms such as genetic algorithm, ant colony algorithm and so on.

Generally, these complex optimization problems can be expressed as follows:

(1)

$$Min \quad f(x)$$

 $x = \{x, x, ..., x\}$

Where f(x) the optimizing problem as non-linear function is, N is the dimension of the functions. The mathematical model of the optimization problem was set up according to formula (1).

More researchers begin to use artificial intelligence algorithms to solve these functions just like formula (1) in general. For example, zhou liang, sun yu, zheng jianguo^[1] proposed a improved pulse

coupled neural network(IPCNN) which can be applied into the processing of digital signal, which means zhou's IPCNN can be used to deal with lots of complex problems such as digital image process. Its experiment shows that the new algorithm PCNN's result is satisfied. However, this new specific PCNN can only be used to solve specific problems, if it is used to handle the other complex problems, this algorithm needs adjust a lot of parameters, which constrains its application.

Genetic algorithm is come from professor Holland and his students in the University of Michigan, they create an adaptive probability optimize technology – genetic algorithm which is based on the mechanism of bio-genetic and evolutionary. Genetic algorithm is a computer simulation of the biological systems.

The research demonstrates that genetic algorithm can retain the optimum individual in the population in order to be capable of convergence to global optima at probability 1. Genetic algorithm has became a sophisticated artificial intelligence algorithms which attracts more attentions in practice, and genetic algorithm is a rapidly growing and efficiency reasoning method in the research of artificial intelligence. However, GA has a lot of problems in evolutionary latter stages, for example, it increases the undulate and premature phenomenon meanwhile decreases the convergent speed greatly. Whitley also pointed out that the most important factors of genetic algorithm are "the diversity of population" and "the pressure of selection" in his paper. And the pressure of selection is too big to lead to the premature^[2].

Artificial immune system(AIS) is studied in order to overcome the above problems in recent years. AIS is a new algorithm as a new direction in the field of computational intelligence research. It originated in 1958 when Burnet proposed clonal selection theory^[3]. The theory of AIS is an important theory of antibody formation in the biological Generally, AIS immunology. simulates the mechanism of vertebrate, especially the senior vertebrate such as human. This new AIS consists of the information processing model of immune system which is based on the immune academic language and some basic related principles in order to construct a new intelligence algorithm for solving complex optimizing problems. Artificial immune system has very strong robustness, fault-tolerance, learning ability and adaptability, and it combines into the advantage of classifiers, neural network and machine reasoning system. This kind of algorithm has been used in many fields, such as machinery automation control, data processing, study. optimization and fault diagnosis and so on. AIS has become a new hotspot after the neural network, fuzzy logic and evolutionary computing in the field of artificial intelligence [4-5].

Artificial immune system is similar to biological immune system (BIS). The process of immune recognition within biological immune system can identify near infinite antigens using a relatively limited antibodies. This is a whole set of mechanism of decomposing complex problems into typical problems and solving them under the resource limited situation. It is a very high efficient mechanism if it is can be introduced into the optimizing field from the viewpoint of information processing. In particular, the clonal selection theory is awaking more and more interest in the community of artificial intelligence scholars. There are a lot of theories within the clonal selection theory such as: the mechanism of recombination, mutation, affinity maturation, receptor editing, and elementary reaction dynamics which can discuss the ability to solve the complex problems effectively. So these theories become the important thought of artificial immune system model and related algorithm.

De Castro proposed clonal selection algorithm in his paper in 2002, which is a typical immune clonal clonal selection algorithm: single selection algorithm (SCSA)^[6]. The new SCSA is based on the

mechanism of affinity maturation and elementary reaction dynamics, which is suitable in the field of pattern recognition, combinatorial optimization, as well as multi-peak function optimization. The SCSA which is proposed by De Castro is still an adventurous and novel attempt, so it has perfect research foreground. Then more and more scholars begin to develop lots of intelligence algorithms based on the immune mechanism, which are used to deal complex optimization with the problem. Subsequently, Kelsey et.al^[7] used a new algorithm: BCA which contains the special mutation operator in order to deal with function optimization. Liu ruochen et.al^[8] proposed a specific binding of lots of kinds of antibody and antigen in order to clone on an antibody, which can embody the collaboration between the antibodies and increase the diversity of population. Then they proposed and described the steps of immune monoclonal strategy algorithm and immune polyclonal algorithm through the mechanism of clonal operator which is based on the antibody clonal selection theory of immunology. Liu ruochen et.al also used Markov stochastic procedures theory to demonstrate the convergence of their algorithm. The simulation result showed that the performance of immune polyclonal algorithm is superior to the traditional evolution strategies and immune monoclonal strategy obviously, and their algorithm which was used to solve the optimizing function is more effective and feasible. Opt-aiNET^[9] algorithm and IGA^[10] algorithm combine the clonal selection theory with immune network theory to improve the efficiency of the immune algorithm; Du haifeng et.al propose an adaptive chaos clonal evolutionary algorithm which is based on the Logistic chaotic sequence^[11]. In addition, Wu zejun et.al. ^[12] propose a new algorithm for solving complex problems based on an artificial immune integration platform, and better result has been achieved by test. On the basis of predecessors' theory, Liu xuezhe et.al.^[13] Propose a new immune algorithm which is based on the improvement of clonal selection theory and the evolutionary mechanism of gene library in 2006, their simulation results is satisfactory.

In addition, the formation of immune recognition ability of biological individual is closely related with the evolutionary process of population gene library. Modern immunology theory thought generally gene recombination is one of the most producing mechanisms with the diversity of single immune system's receptors library, and as the basis of the mechanism of gene recombination, gene library itself is the result of evolutionary learning of the whole population. So the mechanism of learning memory between individual and population in the biological immune system has great inspiration to construct an efficient artificial immune system.

In this paper, some basic knowledge about artificial immune system is introduced in section 2; a new improved immune algorithm based on clonal selection is proposed in section 3; then several complex test functions are introduced in section 4, at the same time, the simulation and test result is given based on the above functions; lastly, section 5 is the conclusion of the paper.

2 Artificial immune system

2.1 Artificial immune system theory

As a certain complex system, biological immune system has a lot of good feature such as distribution, parallelism, self-learning, self-adaptive, self-organization, diversity, dynamic, robust and so on. With the development of multi-interdisciplinary subject intersected by immunology and engineering discipline, artificial immune system was born. Generally, artificial immune system has two branches: firstly, engineering technology is widely applied to construct or simulate immune system and its positive function or characteristic of body, which is conductive to analysis and explain all kinds of inherent mechanism of immune phenomena; the other branch is simulate the part features and principles of immune system in order to constitute a new kind of computing paradigm to solve the complex problems.

Some of these research results in the field of artificial immune system were beginning to become an accepted method in which to deal with complex optimizing problems. In 2000, De Castro ^[14] proposed clonal selection algorithm which is constructed based on the theory of clonal selection. Clonal selection theory is as follows:

When the lymphatic system recognizes the antigen, B cells are activated and proliferating in order to generate B clone cells. Then the B clone cells is through the process of mutation, lastly, they will become the antibodies which is specific to antigen.

Clonal selection algorithm (CSA) is based on above theory. Generally, the optimal solution in the complex problems is as antigen, and the feasible solution is as antibody, then all the antibodies construct an antibody population, which will be evaluated by fitness function. Subsequently, the population is through the operation of clone, mutation and so on in order to make the population move towards the antigen.

In general, the closer antibody move toward antigen, the greater the fitness is. In optimizing, the size of fitness is computed by the value of objective function. Its steps are as follows:

Step1: initialization. Set up the memory unit: P_M . If the memory unit is empty, CSA will generate N antibodies randomly in order to create a antibody population: Pop; otherwise, the number of antibodies in the memory unit P_M is M, and CSA will generate N-M antibodies randomly: P_r , then P_r and memory unit P_M merge together in order to build a new antibody population: Pop;

Step2: evaluation. Compute the fitness of every antibody $anti - p_i$ in the antibody population in order to get the f_i (f_i means the affinity between antibody and antigen), then these antibodies are classified according to their size from small to large;

Step3: selection. The first n antibodies will be selected;

Step4: clone. The antibodies which is selected in step 3 will be cloned in order to get a clone pool: C, and the number of above antibodies is proportionate to the fitness of antibodies;

Step5: mutation. Every antibody in the clone pool C will undergo high frequency mutation in order to generate a new antibody population: N - Pop. Bigger the fitness is, lower the degree of mutation;

Step6: union. To combine antibody population *Pop* with the new antibody population N - Pop, then select the first N biggest antibody which fitness is bigger than others in order to build the new antibody population *Pop*; correspondingly, select the first M biggest antibody which fitness is bigger than others to build the memory unit P_M .

Step 7: replacing. To generate d antibodies randomly, then instead of the last smallest d antibodies which fitness is small than others in the population: *Pop*.

Step 8: judge. The termination condition will be used to check whether it is satisfied. If yes, output the antibody $anti - p_i$ with optimal value of objective function which is as the optimal solution, then stop the iteration of the algorithm; otherwise, go to step 2;

In general, the algorithm can set up an upper

bound of the number of iteration t as the termination condition. From the description of these contents, it may be seen that the core of the algorithm is a mathematical simulation which is based on the antibody clonal selection theory of immunology. As the first modeling of biological immune system, this algorithm is also the most typical artificial immune system algorithm. Most of the follow-up algorithms are improved based on the above model. All of these algorithms are referred as immune optimization algorithms.

Compared with traditional evolutionary algorithm, immune optimization algorithms have adopted the whole search strategy too, and it is focus on information exchange between these individuals, so the traditional evolutionary algorithm and immune optimization algorithm have many similarities. Especially in the whole structure of algorithm, they have been through the following steps:



Fig.1 the steps of these evolutionary algorithms

Because of the structural similarity to traditional evolutionary algorithm, immune optimization algorithm will get the global optimal solution at last; possibly of similar function, immune optimization algorithm have the ability of parallel computing in nature, which means this immune optimization algorithm can reduce the possibility of sinking into local optima effectively, and has the inherent advantages to combine with other intelligent algorithms in order to be more efficiently.

At the same time, the immune optimization algorithm which is based on the artificial immune system combines some advantages of biological immune system, which makes it have a lot of merits as follows: parallelism, adaptive, self-learning, diversity, dynamics, robust and so on. This makes it more superior than the traditional evolutionary algorithm, so that it can be applied in various areas. However, it also has a lot of disadvantages as follows:

On the one hand, the research on the artificial immune system is still in the initial stage, and the mechanism of immune system is very complex, so it is too difficult to simulate this immune system which means that we can not get a complete mathematical model; on the other hand, the mathematical itself has limitation, for example, firstly, it needs a great many of the calculation in order to get the global optima, which will limit the efficiency of the algorithm, secondly, when in the stage of data processing, artificial immune model can only concentrate the data sample, which means it can only obtain the feature points in the solution space; thirdly, the immune model will be trapped into the local optimal solution in the later period.

Form that point, this paper presents a new and uniform computing criteria in order to simulate the complex biological immune system clearly. At the same time, this paper analyzes the structure of this algorithm based on understanding the implementation process in order to search the bottleneck of this algorithm, and therefore provides the theoretic foundation for this new immune algorithm.

2.2 The structure of anti-idiotype

Zhang lining et.al proposed there was a new structure based on the immunology^[15]. They notice that in the biological immune system, antibody is a kind of molecule of a protein which is generated by B cells. B cells can recognize the antigen then clone, proliferate in order to differentiate into plasma cell, and the plasma cell will generate above molecule of protein, which is also called immunoglobulin molecules. The antibody will combine with the antigen which is inbreaked by the external infection micro-tissues or toxicant, then antibody can destroy these antigen with the help of other factors such as T cells, MHC class molecules and so on in the immune system in order to reduce the menace to the human body. In general, antibody is divided into two distinct functional areas: one is a constant area which can keep relative static environment, which is called C area for short; while the other is a variable area which is responsible for combination with different kinds of infection antigen, which is called V area for

short. Basically, the variable area is concerned about the combination with antigen; while constant area is interacting with the receptor on the host cells. The constant area has a limited change; and the change on variable area makes the whole immune system have management capability and can solve problem. The research on the stage of immune response shows that this stage can generate diversity of antibody, and the mutation of somatic cell in variable area tends to increase as the time increases, that is to say, the variable area provides the robust and adaptive capability for immune system.

Generally, antibody consists of antibody determinants and idiotype. The research on biological immune mechanism shows that the closer the match between the antibody and antigen, the greater the strength of molecular combination, the better the recognition effect. Antibody can combine with other antibodies, too. Because antibody not only contains antibody determinants but also antigen determinants. that means idiotype antigen determinants which is called idiotype for short. Zhang lining et.al notice that different specific antibodies have the different idiotype antigen determinants, which can not only inspire different species or different individuals belonging to the same species in order to generate corresponding antibody, but also stimulate other clone cells to generate idiotype antibody in its body. Therefore, idiotype antibody plays an important role in immune system, for example, it can recognition the antigen, generate the antibody, and destroy the antigen and so on.

In this paper, an algorithm is proposed based on above immune theory and its related mechanism in order to design a new artificial immune algorithm.

3 A New Immune Algorithm based on the new structure

3.1 mechanism analysis for the new immune algorithm

According to traditional Burnet's antibody clonal selection theory and above mentioned content which is related to the structure of anti-idiotype in the biological immune system, this paper proposes a new artificial immune algorithm (IAAI).

This new immune algorithm simulates the biological mechanism of immune system, and its status transfer diagram is as follows:



Fig.2 the status transfer diagram

The following is a concrete description for fig.2: (1) Dynamic clone proliferation

The process of clone proliferation is a process of obtaining a right scale of clone. In general, the clone proliferation operator is defined as follows:

 T_c^C

Clone proliferation operator T_c^C can be described as follows:

$$T_{c}^{C}(A(k)) = [T_{c}^{C}(a_{1}(k)), T_{c}^{C}(a_{2}(k), ..., T_{c}^{C}(a_{NP}(k))]^{T}$$

Where $T_{c}^{C}(a_{i}(k)) = I_{i} \times a_{i}(k)$
 $i = 1, 2, ..., NP$

And *NP* is the size of the population, I_i is a q_i -dimensional row vector, and its element is 1, it is also called q_i clone of antibody $a_i(k)$.

In most cases, the size of clonal antibody is always proportionate to the fitness of antibody. That is to say, the bigger the fitness of antibody it is, the greater the chance to make local search is. Therefore, q_i can be decided as follows:

① Antibody affinity function

Antibody affinity function is the fitness of objective functions. It can be used to judge the quality of candidate solution. So it is listed as:

affinity $(a_i(k))$

In general, $affinity(a_i(k))$ is corresponded to the objective function in the optimization of the

engineering problems.

According to the antibody affinity function, a weight is defined as follows:

$$W - affinity(a_i(k)) = \frac{affinity(a_i(k))}{\sum_{j=1}^{NP} affinity(a_j(k))}$$
(2)

2the scale of clone

$$q_i = Int(NC \times W - affinity(a_i(k)))$$
(3)

Generally, NC is a constant which is related to the scale of clone. NC will meet the following requirements with different clone population:

NC > NP

In addition, considering the traditional immune algorithm will fall into the local optimum in the later running stages. In this paper, NC will increase in linear-shaped channel in order to increase diversity of the clone population and avoid premature. The concrete steps as follows:

Step1: To compute the average value of antibody affinity in the process of this algorithm iteration every time. For example, the k th iteration is as follows:

$$avg-affinity(a_{i}(k)) = \frac{\sum_{j=1}^{q_{i}} affinity(a_{ij}(k))}{q_{i}} \qquad (4)$$

Step2: If

$$|avg - affinity(a_i(k)) - avg - affinity(a_i(k-1))|$$

< E

Where ε is a constant based on the calculation precision of objective function. Then $NC = \alpha \times NC$

Where α is a fixed constant. In this paper, $\alpha = 1.2$ However, the efficiency of solving problem by this new algorithm will decrease as the scale of the population bigger. In order to avoid this occur, if

 $\begin{vmatrix} avg - affinity(a_i(k)) - avg - affinity(a_i(k-1)) \end{vmatrix} \ge \varepsilon$ $NC = \beta \times NC$

Where β is a fixed constant in this paper, and $\beta = 0.8$.

In this way, the clone population will be adjusted by above mentioned formulas as follows:

$$A'(k) = \{a'_{1}(k), a'_{2}(k), ..., a'_{NP}(k)\}$$

Where
$$a'_{i}(k) = \{a_{i1}(k), a_{i2}(k), ..., a_{iq_{i}}(k)\}$$

And
$$a_{ij}(k) = a_{i}(k) , j = 1, 2, ..., q_{i}$$

(2) Improved anti-idiotype mutation

As mentioned above, if B cells can combine with antigen in the artificial immune system, they will be activation, and then cell division at high frequency. This process can be seen as high frequency mutation of body cells, which is an important mutation in the stage of clone proliferation. At the same time, according to the theory of above mentioned anti-idiotype structure, antibody variable area can offer the ability in robustness and self-adaptability in immune system. When antigen determinants find its match, it not only stimulates the individuals to generate corresponding antibody, but also stimulate other clone B cells to generate anti-idiotype individuals in its body in order to destroy the antigen. The mutation operator in this paper is improved based on the above proposed Zhang Lining et.al's theory^[15]. This improved mutation operator is called anti-idiotype mutation operator as follows: T_m^C o

Zhang Lining et.al proposed that the population which had been through clone proliferation would make anti-idiotype mutation operation based on the probability P_m^i . Then we can get:

$$A''(k) = T_m^C(A'(k))$$

Concretely, for any antibody $a_{ij}(k)$ in this population, *i* represents the scale of antibody population, $i \ge 3$, and *j* represents the scale of clone, according to zhang lining's theory, the final mutation should follow the description below:

$$a_{ij}(k) = a_{ij}(k) + \upsilon \times (a_{r1j}(k) - a_{r2j}(k))$$
(5)

Where i, r_1, r_2 are three unequal integers, $v \in [0,1]$, v is a function coefficient, v can express the strength of inhibition when anti-idiotype generate new antibody.

In theory, the structure of anti-idiotype can give us an excellent food for thought, just as above formulas, zhang lining et.al use anti-idiotype mutation operation, which use the information of antibody, and adopt margin to obtain the anti-idiotype structure information of antibody, then to guide these antibodies mutation.

However, there are two problems in zhang's theory :

(1) The confirmation of function coefficient v do not have a reliable theory, it is decided by experience. So this make zhang's algorithm be confronted whit great limitation when its algorithm is applied in optimizing problems.

2 there is a value as differences between different

antibodies, it can provide a channel for the antibodies' evaluation. However, it can not guide these individuals after mutation to close up the optimal point in the solution space. In this paper, an improved anti-idiotype mutation operator is proposed:

① Find the antibody $a_m(k)$ corresponding to current optimum affinity. Then get :

 $affinity(a_m(k)) = \max$

{affinity(
$$a_1(k)$$
), affinity($a_2(k)$),..., affinity($a_{NP}(k)$)}

② To define a weight based on the antibody affinity function:

$$W - affinity(a_i(k)) = \frac{affinity(a_i(k))}{\sum_{j=1}^{NP} affinity(a_j(k))}$$

③ The final mutation is below:

$$a'_{ij}(k) = a_{ij}(k) + W - affinity(a_i(k)) \times |a_m(k) - a_{ij}(k)|$$

We can see that these antibodies after mutation will offer an effective channel for the evaluation of the population through importing the anti-idiotype structure information.

(3) Dislocated linear recombinant

As set forth, when artificial immune algorithm is in computing, it is easy to get into the local best. So in this paper, a dislocated linear recombinant is proposed in order to avoid premature phenomenon. This operator is called T_x^C which can be used to increase the diversity of the population. At the same time, the objective of recombinant operation is to make sure that regeneration of individuals can better reflect the father antibodies' character.

If the possibility of recombinant is p_R , then the operator of dislocated linear recombinant is below:

$$A^{'''}(k) = T_x^C(A^{''}(k))$$

The design idea of this operator is similar to the traditional cross operator in artificial immune algorithm. Traditional cross operator will operate on two father individuals; however, different from traditional cross operator, in this paper, the operation of recombinant will operate on the father antibody and its corresponding individual which has been through mutation. The specific operation is as follows:

$$a_{ij}''(k) = a_{ij}(k) \times p_R + a_{ij}'(k) \times (1 - P_R)$$
(6)

From formula (6), we can find that the antibody can keep its own advantages after dislocated linear

recombinant; at the same time, this dislocated linear recombinant can make sure the diversity of population.

(4)Clone selection

The population after dislocated linear recombinant will build a new population. Firstly, in the condition of the value of affinity, the sequence from high to low, then select the next generation antibody population which has the same number with the senior generation. It can be described as T_s^C :

$$A(k+1) = T_s^C (A(k) + A^{'''}(k))$$

Analysis of above steps can see that this new algorithm has following advantages:

Firstly, the premature phenomena can be avoided effectively, because the diversity of the population can be ensured; secondly, in the process of iteration, the whole population can be guided to the optimal point in the solution space effectively, and then help the population to find its global optimal solution.

3.2 Steps of new immune algorithm

In this paper, all the test problem and their constraint conditions are recorded as antigen F(*). Initial antibody is generated randomly, and this new algorithm uses real-coded schema. The antibody population is as follows:

$$A = \{a_1, a_2, ..., a_{NP}\}$$

So, the algorithm flow of this new algorithm is below:

Step1: To initialize the parameters of this algorithm. The number of iteration is k, original k is 0. Initialization of antibody population is A(k), its size is NP. Constant NC is related to the scale of clone. The probability of recombination is p_R , the probability of mutation is p_M , function coefficient is υ ;

Step2: If antibody population can satisfy solving condition equations or the iteration times are to the highest extent, then stop the algorithm, and output the best individual in population A(k); otherwise go to step 3;

Step3: antibody population A(k) performs the operation of dynamic clone proliferation: T_c^C ; then a new antibody population A'(k) is built;

Step4: antibody population A'(k) performs the operation of improved anti-idiotype mutation: T_m^C ;

then a new antibody population A''(k) is built;

Step5: antibody population $A^{"}(k)$ performs the operation of dislocated linear recombinant: T_x^C ; then a new antibody population $A^{"}(k)$ is built;

Step6: antibody population A''(k) performs the operation of clone selection: T_s^C ; then a new antibody population A(k+1) is built;

And k = k + 1, go to step 2.

4 Experiments and Results

In order to evaluate the performance of this new immune algorithm, in this paper, two other algorithms are listed below as comparison.

① Quantum evolutionary algorithms(QEA)

② Quantum-inspired hybrid evolutionary method^[16] These two algorithms are described below:

(1)QEA: As a new research field, QEA has been widely applied in dealing with complex problems; it combines the quantum computing with evolutionary algorithm, and it is based on the quantum superposition state and quantum computing. It has perfect global search ability.

(2)I-HQEA: In Liu zhonggang and Zhou Liang's paper^[16], the authors present an improved hybrid intelligent algorithm based on quantum evolution algorithm, which is ameliorated from the mechanism of quantum evolutionary algorithm in order to construct a new improved hybrid quantum evolutionary algorithm(I-HQEA). Then this new algorithm is used in solving the multi-modal function optimization, the simulation result is very encouraging.

Firstly, In order to verify the validity of the I-HQEA, in this paper, three functions are chosen to be testified according to the references (17) and (18).

Sphere function is a continuous, simple single-state function, which is usually used to analyze the implementation performance of the algorithm; Rosenbrock function is a classic complex optimization problem, its global optimization is in a smooth, long and narrow parabola-shaped valley, which means it is difficult to search the global optimization, so Rosenbrock function is usually used to evaluate the implementation efficiency of the algorithm; Rastrigrin function is a typical nonlinear multi-state function, which has a wide range of search space, and a large number of local minimum point, so it is usually considered to deal with the complex multi-state issues.

sphere function :

$$f_1(x) = \sum_{i=1}^n x_i^2$$
, $x \in [-100, 100]$

Rosenbrock function

$$f_2(x) = \sum_{i=1}^n (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2) ,$$

 $x \in [-100, 100]$

Rastrigrin function

$$f_3(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10) ,$$

 $x \in [-10, 10]$

The theory value of above functions is zero. In this paper, I-HQEA, QEA, and the new immune algorithm(NIA) are selected to participate in the experiment in order to compare with each other. Population size is 50 and 100 separately, corresponding to table 1 and table 2, the largest number of iterations is 1000.

From the table 1 and the table 2, it shows that I-HQEA, QEA and NA can get the effective result when it is used to deal with the single-apex function. When it is in dealing with other 2 complex functions, NA can get more effective results then I-HQEA and QEA. The reason is that NA uses a new structure of immune system; it can increase the diversity of population, then NA can find the optimization solution with biggest probability. All of this demonstrates NIA is more suitable for dealing with the complex optimization problem than QEA, and I-HQCA, and shows that the performance of NIA is more superior to that of QEA, and I-HQCA in terms of the global search capability and the ability of possessing exploration.

In order to test performance of the new immune algorithm in this paper better, a group of complex multi-peak functions in zhang lining's papers^[15] for test. They are listed below:

$$f_4(x) = \sum_{i=1}^n \frac{x_i^2}{4000} - \prod_{i=1}^n \cos(\frac{x_i}{\sqrt{i}}) + 1$$

$$f_5(x) = \sum_{i=1}^n (x_i^2 - 10\cos(2\pi x_i) + 10)$$

$$f_6(x) = \sum_{i=1}^n (y_i^2 - 10\cos(2\pi x_i) + 10)$$

$$y_i = \begin{cases} x_i & |x_i| < 1/2\\ \frac{round(2x_i)}{2} & |x_i| \ge 1/2 \end{cases}$$

$$f_7(x) = \sum_{i=1}^{10} \frac{y_i^2}{4000} - \prod_{i=1}^{10} \cos(\frac{y_i}{\sqrt{i}}) + 1$$

$$y = M \times x$$

Where M is a rotated matrix, and f_4 , f_5 , f_6 , f_7 are all 10-dimensional function, that is to say, n = 10, and their optimum value is 0.

The testing function f_4 , f_5 , f_6 , f_7 uses the algorithm AICSA which is proposed by zhang Lining, Gong Maoguo, Jiao Licheng, Ma Wenping in their references (15), they pointed out that AICSA can search in one or more directions around antibody. So AICSA can do the local research and global research simultaneously, which make AICSA have the strong and overall searching ability. Based on this, the new immune algorithm is compared with AICSA in this paper in order to test their performance. The statistical results of AICSA are corresponding to Zhang Lining's literature^[15].

The simulation divides into 3 parts. Firstly, these complex multi-peak functions will be tested; secondly, the result is found in 30 tests by new immune algorithm and AICSA; thirdly, get the statistical results.

① the test results of f_4 , f_5 , f_6 , f_7 when n = 10. The terminating condition is that the maximum calculation number is 3000. From table 3, the test results are given by new immune algorithm and AICSA based on 30 independent trials randomly. It is concluded from the test result in table 3 that the new immune algorithm gains good results when it is used to deal with solving function, especially complex function. This is because the new immune algorithm adjusts the operator in order to make sure new immune algorithm can have good global search capability.

② the test results of f_4 , f_5 , f_6 , f_7 when n = 30. Depending on the complexity of the test function, the terminating condition is that the maximum calculation number is 10000. From table 4, the test results are given by new immune algorithm and AICSA based on 30 independent trials randomly.

A look at the table 4 indicates that the results are similar with results in table 3. Both of AICSA and NIA gain encouraging results when they are used to solve functions f_4 , f_5 , f_6 , f_7 . However, the experiments show that the speed and veracity after operation of NIA is improved by far than the AICSA. This indicates that the design of NIA can improve the diversity of population as a goal, and its operator can guide the algorithm close to the optimal solution. All

of these make sure that the algorithm which is proposed in this paper can have a good enough solving ability and strong robustness.

Table 1 statistical results for functions

Function	Algorithm	Average Value	Iteration
f_1	I-HQEA	0	500
	QEA	0	1000
	NIA	0	500
f_2	I-HQEA	6.0221	500
	QEA	31.5779	1000
	NIA	4.3236	500
f_3	I-HQEA	0.8824	500
	QEA	3.4430	1000
	NIA	0.4428	500

Table 2 statistical results for functions

Function	Algorithm	Average Value	Iteration
f_1	I-HQEA	0	500
	QEA	0	1000
	NIA	0	500
f_2	I-HQEA	1.2263	500
	QEA	10.9682	1000
	NIA	1.1453	500
f_3	I-HQEA	0.2241	500
	QEA	3.6730	1000
	NIA	0.0876	500

Table 3 statistical results for 10-D functions

Function	Algorithm	Average Value	Std
f_4	AICSA	2.72e-002	3.90e-002
	NIA	3.06e-002	3.22e-002
f_5	AICSA	0	0
	NIA	0	0
f_6	AICSA	0	0
	NIA	0	0
f_7	AICSA	1.93e-001	1.22e-001
	NIA	1.77e-002	2.38e-002

Table 4 statistical results for 30-D functions

Function	Algorithm	Average Value	Std
f_4	AICSA	0	0
	NIA	0	0
f_5	AICSA	0	0
	NIA	0	0
f_6	AICSA	0	0
	NIA	0	0
f_7	AICSA	1.24e-009	158e-009
	NIA	2.81e-010	3.63e-010

5 Conclusions

In this paper, a lot of theories such as the biological immune mechanism, the clonal selection theory, anti-idiotype structure of immune system and so on are introduced, and a new immune algorithm is proposed based on above theory. There are four operators in this paper: dynamic clone proliferation operator; improved anti-idiotype mutation operator; dislocated linear recombinant operator; and clone selection operator. These operators can make the algorithm keep the diversity of population which can avoid premature of the population; at the same time, the design of operators has a heuristic rule which can guide excellent clone antibody in the population towards optimum solution in the iterative process. All of these can make sure that the new immune algorithm be capable of convergence to global optima at biggish probability.

Theoretical analysis and experimental results show that the performance of new immune algorithm surpasses effective QEA and I-HQEA which is proposed by Liu Zhonggang, Zhou Liang when they are applied into solving sphere function, Rosenbrock function and so on. When the new immune algorithm is compared with AICSA which is proposed by Zhang Lining, Gong Maoguo, Jiao Licheng, Ma Wenping to solve the complex and high-dimensional functions, the new immune algorithm has more good robust and solving performance.

In this paper, the simulation results show that the existing artificial immune algorithm is improved through adjusting its mechanism, for example, the new mechanism can be imported such as anti-idiotype structure. These have some positive significance in relation to improving the algorithm's solving accuracy, especially its robustness in dealing with complex function; at the same time, a new direction is pointed out in the future based on the artificial immune algorithm. considering richer immune mechanism such as T cells, MHC and so on, which can be imported into new artificial immune model in order to improve the performance of the algorithm further.

References:

- Zhou liang, Sun Yu, Zheng jianguo, Automated Color Image Edge Detection using Improved PCNN Model, WSEAS Transactions on Computers[J], 7(4), 2008: 184-189
- [2] Che Ming, Sun Xiaohua, Han Qianqian, Disadvantages of the genetic algorithm

compared with biologic evolution and improvement[J]. Micro Processors, 2006, 56(2):56-58

- [3] Burnet F M, the Colonal Selection Theory of Acquired Immunity[M]. Cambridge University Presss, 1959
- [4] Dasgupta D, Forrest S. Artificial immune systems in industrial applications. In: Meech JA, Veiga MM, Smith MH, LeClair SR, eds. Proc. of the 2nd Int'l Conf. on Intelligent Processing and Manufacturing of Materials. Piscataway: IEEE Press, 1999. 257–267.
- [5] Jiao LC, Du HF. Development and prospect of the artificial immune system. Acta Electronica Sinica, 2003, 31(10):1540–1548 (in Chinese with English abstract).
- [6] Castro L N De .Learning and optimization using the clonal selection principle[J]. IEEE Trans Evolutionary Computation, Special Issue on Artificial Immune Systems, 2002, 6(3): 233-239
- [7] Kelsey J, Timmis J. Immune inspired somatic contiguous hypermutation for function optimization[C], Proceedings of the Genetic and Evolutionary Computation Conference. Heidelberg: Springer Verlag, 2003, 2723 : 207-218
- [8] Liu ruochen, Du haifeng, Jiao licheng, Immune Poly-Clonal Strategies[J], Journal of Computer Research and Development, 2004, 41(4):571-576,55
- [9] de Castro L N, Timmis J. An artificial immune network for multimodal function optimization[C], Proceedings of the 2002 Congress on Evolutionary Computation, Honolulu: IEEE Press, 2002: 669-674
- [10] Luo W J, Cao X B, Wang X F, An immune genetic algorithm based on immune regulation[C], Proceedings of the 2002 Congress on Evolutionary Computation, Honolulu: IEEE Press, 2002:801-806
- [11] Du haifeng, Gong maoguo, Liu ruochen, Jiaolicheng, An Adaptive chaos clonal evolutionary Programming algorithm[J], Science in China, Ser.E, 2005, 35(8):817-829
- [12] Wu Zejun, Liang, Yiwen, Integrated Platform of Artificial Immune System for Anomaly Detection[J], WSEAS Transactions on Information Science and Applications, 2(2), 2005:144-149
- [13] Li Xuezhe, Pu Qiangguo, Mastorakis Nikos, The

immune algorithm and its application to blood pressure measuring[J], WSEAS Transactions on Electronics, 3(5), 2006: 288-292

- [14] De Castro L N, Von Zuben F J, The clonal selection algorithm with engineering applications: workshop Proceedings of GECCO[C], 2000:31-37
- [15] Zhang Lining, Gong Maoguo, Jiao Licheng, Ma Wenping, Clonal Selection Algorithm Based on Anti-Idiotype[J], Journal of Software, 20(5), 2009:1269-1281
- [16] Liu zhonggang, Zhou liang, A Quantum-inspired Hybrid Evolutionary Method, proceedings of the 8th WSEAS international conference on applied computer and applied computational science, 2009:422-425
- [17] Gan Changsheng, Zhou Liang, A New Quantum Clonal Algorithm, Proceedings of the 5th WSEAS International Conference on Mathematical Biology and Ecology, 2009:93-97
- [18] Gan Changsheng, Hong Juan, Zhou Liang, A New Hybrid Quantum Evolutionary Algorithm and Its Application, Proceedings of the 5th WSEAS International Conference on Mathematical Biology and Ecology, 2009: 98-102