A NEW ARTIFICIAL IMMUNE AIGORITHMFOR SOLVINGFUNCTION OPTIMIZATION PROBLEMS

[1]ZHI XU, [2]DEMING ZHONG, [3]YUXIN DING, [4]YUKUN ZHAO

[1,2,3,4]School of Reliability and Systems Engineering, Beihang University, Beijing, China
E-mail: [1]a332999245@gmail.com, [2]zhongdeming@buaa.edu.cn,[3]18086745672@163.com,[4]814361799@qq.com

Abstract - To overcome the drawbacks of Simple Genetic Algorithm (SGA) and Particle Swarm Optimization (PSO) in multi-peak function optimization, such as insufficient diversity and local optimization tendency, a new artificial immune algorithm (IAIA) is proposed. Based on the traditional framework of the artificial immune algorithm, the algorithm redesigns the two key clone and mutation operators to address these drawbacks. Last, test functions were used to compare the IAIA with the SGA and the PSO. The research results showed that the IAIA algorithm has certain advantages in both convergence speed and accuracy in solving such optimization problems.

Keywords - Immune algorithms, multi-peak function, clone selection, Thermal Fatigue, function optimization.

I. INTRODUCTION

After applying a number of mathematical models, the practical problems can be abstracted as numerical function optimization problems[1]. Because of the universality and importance of such problems, they have been extensively studied in recent years. For the single peak function optimization problem, the convergence of the algorithm is very important; for multi-peak function optimization, the rapid convergence of the algorithm is required, but finding the globally optimal solution is more important to avoid falling into a local extreme point.

Although Simple Genetic Algorithm (SGA) and Particle Swarm Optimization (PSO) are traditional algorithms used to solve such problems, these two algorithms have drawbacks. SGA [2-3] easily falls into the local optimal solution in the process of solving a multi-peak function. Similarly, for a search space of more local extreme points, the searching efficiency of PSO[4] may suddenly decrease and not be high near the optimum point. Thus, we must develop a new algorithm that can solve the multi-peak function optimization problem and overcome the related shortcomings, such as insufficient diversity and local optimization tendency.

The artificial immune algorithm(AIA) [5], which is based on the evolution and immune mechanisms that promote high-affinity antibodies and deemphasize antibodies with high concentrations, is a type of optimization algorithm that is built for the purpose of the maintenance of antibody diversity. In general, AIA compares objective functions and constraints for solving the actual problems to the antigen and compares the feasible solution of the objective functions to antibodies; thus, the function value of the feasible solution is based on the affinity between an antibody and an antigen. AIA always gives priority to selecting the antibody with high affinity and low concentrations into the next generation of antibodies to reach the goal of promoting the antibody with higher affinity and deemphasizing the antibodies with higher concentrations. In the evolutionary process, antibody diversity is fully maintained while avoiding the local optimum effectively, thereby improving the local search ability and speeding up the convergence of the algorithm. The advantages of the AIA itself allow a new direction for solving multi-peak function optimization problems.

II. A NEW ARITIFICIAL IMMUNE ALGORITHM (IAIA)

2.1. Algorithm

In this paper, based on the clonal selection principle, a new artificial immune algorithm (Improved Artificial Immune Algorithm, IAIA) using binary code and combining the framework of the traditional immune algorithm, a newly designed clone selection operator and a new mutation gene operator is implemented in the MATLAB programming environment. This algorithm fully maintains the diversity of antibodies and avoids the local optimum effectively in the evolutionary process.

Step 1: Randomly select an antigen $Ag_i$from the identified antigens of a group and supply it to the initial antibodies Ab_0. Initial antibodies $Ab_0$are represented by a random matrix generated through the RAND function in 0-1 that has the antibodies scale as the rows and the binary string length of antibodies as the columns.

Step 2: Calculate the affinity between all the antibodies from Ab_0 with Ag_i.

The Hamming distance (D) between the antigen (Ag) and each of the antibodies (Ab) is used to measure the affinity.

$$D=\sum_{i=1}^{L}\delta_i,\ \delta_i=\begin{cases}1, & \text{If } Ab_{ki}\neq Ag_{ji}\\ 0, & Else\end{cases} \quad (1)$$

In the formula, L is the length of the string to the antibody.

Step 3: N antibodies from Ab_0 with the highest affinity form the antibodies $Ab_j(n)$.
Step 4: The new antibodies C_j are formed by cloning the N antibodies from step three based on their affinity, and antibodies with higher affinity will replicate more of the same individuals.
Step 5: The antibodies C_j' are formed by mutating C_j; the mutation rate is in inverse proportion to the affinity of the individual.
Step 6: Calculate the affinity between all the antibodies from C_j' with Ag_i.
step 7: Select the antibodies with the highest affinity from C_j'; if its affinity is higher than the others from original antibody group $Ab_j(n)$, then the original antibodies will be replaced with the mutated antibodies.

In accordance with the above steps, when each antigen is presented to the antibodies, an iteration is completed. When the satisfactory solution is attained after N times of performing iterations, the algorithm ends; at this point, the set of antibodies Ab(n) is the optimal solution.

2.2. Clonal Selection Operator

An important step in the artificial immune algorithm is cloning those high-quality individuals. Clonal operator can copy some good antibodies and improve the initial antibodies. The clonal selection operator in this paper is proposed as follows: Assume n antibodies with the highest affinity are arranged in an ascending order. For all selected antibodies, the number of produced clones is given as follows:

$$Nc = \sum_{i=1}^{n} \text{round}\left(\frac{\beta \cdot N}{i}\right) \quad (2)$$

In the formula, the parameter Nc is the total number of clones from all selected antibodies, β is a magnification coefficient, N is the total number of antibodies, i is the sorting subscript for the selected antibodies,round() is the rounding operator. Higher affinity antibodies correspond to a higher number of clones, and vice versa; a lower affinity corresponds to fewer clones.

2.3. Mutation Operator

Genetic variation, which is an important operation in IAIA, can prevent the algorithm from prematurely ending as well as improve the search capabilities of the solution space and maintain the diversity of antibodies. Regarding the mutation operator, this paper introduces the concept of a mutation threshold, which can control the scope of variation, thus not only maintaining the high speed of the algorithm but also ensuring the diversity of antibodies. The practical operation is as follows:

$$M = \text{rand}(\text{size}(T, 1), n) \leq \text{pMutate} \quad (3)$$
$$M = T - 2 \times (T \times M) + M \quad (4)$$

In the formula, pMutate is the mutation rate, which is equivalent to the variation of the threshold.T is the number of antibodies that exist after the cloning process.

III. SIMULATION EXPERIMENT

3.1. Function and Parameter Setting

The four multi-peak value test functions are as follows:

$F1 = \sin X \quad (5)$

Value range: $-1 \leq X \leq 2$; Maximum value: 1

$F2 = \sin(\frac{1}{X}) \quad (6)$

Value range: $-1 \leq X \leq 2$; Optimal solutions: 1

$F3 = X \sin(10\pi X) + 2 \quad (7)$

Value range: $-1 \leq X \leq 2$; Maximum value: approximately 3.8

$F4 = X + 10 \sin(5X) + 7 \cos(4X) \quad (8)$

Value range: $-1 \leq X \leq 2$; Maximum value: approximately 15

To ensure accuracy and persuasiveness, all the algorithm parameters must be set to the optimal value before comparing the advantages of the three algorithms considered. The setting of the key operators of the IAIA is performed as follows:

The setting of the clone operator parameterβ:

The magnification parameter β is an important parameter that is used to ensure the number of clones is proportional to the affinity.After changing parameter β separately, the trends of the optimal value and the running time are observed. The obtained data are presented in**Table 1.**

Based on the Table 1, with the parameter β increasing, the optimal value and the running time are all increasing, i.e., the greater the parameters are, the better the results with increasing running time are. After comprehensive consideration of the results, the parameter β is set to 0.2.

β	0.01	0.05	0.1	0.2	0.8
Optimal value	3.4587	3.7824	3.8502	3.8503	3.8503
Running time	1.3958 s	1.4976 s	1.5816 s	1.7899 s	3.7166 s

Table 1: The effect of parameter β on the IAIA

pMutate	0.01	0.05	0.1	0.2	0.8
Optimal value	3.8426	3.8501	3.8503	3.8503	3.8503
Running time	1.7772 s	1.7834 s	1.7857 s	1.8145 s	1.8290 s

Table 2: The effect of parameter pMutate on the IAIA

Function	Optimal value	Worst value	Average optimal value	Running time
F1	1	1	1	1.584 s
F2	1	1	1	1.624 s
F3	3.8503	3.8501	3.8503	1.9533 s
F4	18.5722	18.5722	18.5722	1.6683 s

Table 3: The outcomes of running the IAIA ten times

Function	Optimal value	Worst value	Average optimal value	Running time
F1	1	0.9962	0.9991	29.841 s
F2	1	0.9974	0.9992	33.896 s
F3	3.8502	3.7789	3.8411	33.640 s
F4	18.5722	18.5677	18.5985	38.477 s

Table 4: The outcomes of running the SGA ten times

Function	Optimal value	Worst value	Average optimal value	Running time
F1	1	0.9953	0.9991	0.289 s
F2	1	0.9958	0.9990	0.296 s
F3	3.8501	3.7562	3.8378	0.563 s
F4	18.5722	18.5663	18.5952	0.4479 s

Table 5: The outcomes of running the PSO ten times

The setting of the mutation operator parameter pMutate:

The parameterpMutate is similar to a mutation threshold, which is related to the mutation rate directly. Similar to the process described above, after changing pMutate separately, the trends of the optimal value and the running time are observed. The obtained data are presented in Table 2.

With the increase in pMutate, the optimal value improves, whereas the running time is barely affected overall. This result indicates that the design concept of the mutation operator is relatively simple and convenient. Because the optimal value remains basically unchanged when pMutate is 0.1 and above, the parameter pMutate is set to 0.1.

3.2. Simulation Result

Under the condition of the given parameters for which the population size is set to 100 and the number of iterations is set 50, these four functions are run ten times separately in the three algorithms to obtain the optimal value, the worst value and the running time of each function and to calculate the average optimal value. The details are shown in table 3, table 4,and table 5.

3.3. Results and Discussion

Based on comparison of the IAIA with the SGA and the PSO in 4 dimensions, i.e., the optimal value, the worst value, the average optimal value and the running time, the following observations are made:

1. Optimization results

Examining the results from the statistical data, all the algorithms were able to achieve the optimal value of the function. However, examining the average of optimal values, the IAIA algorithm is better.

2. The ability of escaping from a local optimum

In the process of optimizing the function, based on analysis of the results, we can see that both SGA and PSO become trapped in a local optimum to varying degrees, whereas the IAIA is better than the other two algorithms in achieving the global optimum. This result shows that IAIA is a global optimization methodand is effective in solving the two-dimensional multi-peak function optimization problem.

CONCLUSIONS

This paper proposed an algorithm for solving multi-peak function optimization known as the Improved Artificial Immune Algorithm (IAIA), which is based on the clonal selection principle of an artificial immune system, This algorithm, which involves optimization of the clone operator and mutation operator based on the traditional immune algorithm framework, can efficiently overcome the relevant problems, such as the lack of diversity and the ease of falling into a local optimum. Finally, based on comparison of the performances of 3 algorithms, the IAIA was found to have a strong ability to solve the problem of multi-peak function optimization and thus achieve the global optimum stably and rapidly.

ACKNOWLEDGMENTS

This research was supported by grants from Civil Aviation Joint FundsEstablished by National Nature Science Foundation of China and CivilAviation Adminstration of China(No.U1533201), from a project of Ministryof Industry and Information Technology of China (No.JSZL2015601C008)and from the Major State Basic Research Development Program of China(973 Program) (No. 2014CB744904).

REFERENCES

[1] Jin Z, Fan H. An Improved Immune Genetic Algorithm for Multi-peak Function Optimization[C]// International Conference on Intelligent Human-Machine Systems and Cybernetics. IEEE, 2013:504-507.

[2] Rudolph G. Convergence analysis of canonical genetic algorithm. IEEE Trans Neural Netw[J]. Neural Networks IEEE Transactions on, 1994, 5(1):96-101.

[3] Sheng Z B. Application of Genetic Algorithm in Function Optimization[J]. Journal of Weinan Normal University, 2013.

[4] Qiao J, Wang C, Wei J. An Adaptive Particle Swarm Optimization Algorithm with Local Search[J]. 2015.

[5] Castro L N D, Timmis J I. Artificial immune systems as a novel soft computing paradigm[J]. Soft Computing, 2003, 7(8):526-544.

★★★