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Optimization Design of Manipulator Based on the Improved Immune Genetic Algorithm

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Abstract: *In order to further improve the design effect of rolling transport mechanism of manipulator, an improved immune genetic algorithm (IIGA) is introduced to execute the optimization design in this paper. Aiming at the shortages of blind search and weak local optimization ability of genetic algorithm (GA), inspired by the antibody diversity in biological immnue system, the information entropy is used to construct the expected reproduction rate of antibody, and then the antibodies are selected reasonably. In addition, a memmory base is also used to improve the population diversity. Compared with the genetic algorithm, the simulation results of function optimization show that the IIGA is characterized by strong global optimization ability and quick convergence speed, and the local convergence is solved well. The optimization results of manipulator not only verify the validity of the IIGA, but also show its stronger optimization ability than GA.*
Keywords: *Genetic algorithm, Immune, Optimization design, Manipulator*

I. Introduction

With the development of information technologies, some intelligent optimization algorithms are emerging. Genetic algorithm is one of the famous algorithms and is inspired by Darwin's theory of evolution and Mendel's genetic law. The Genetic algorithm is characterized by global optimization, parallel search, and good robust. Now, the GA has been widely applied to engineering optimization. In order to improve the vibration damping characteristics of passive constrained layer damping cylindrical shell and solve the rational distribution problem of the constrained layer, Shi *et al.* [1] proposed an optimization design method based on the multi-objective genetic algorithm. In order to design soft-switching parameters to ensure the converter operates properly and efficiently, the genetic algorithm is used to roughly optimize the RSM model and accurately optimize SPICE model, respectively [2]. In order to plan out a reasonable path for manipulator to increase the productivity of the manipulator, using improved crossover operator and mutation operator, an improved genetic algorithm is proposed in [3] and the simulation results show its validity. A lot of research results show that the genetic algorithm has stronger optimization capabilities and better robustness; however some of deficiencies such as local convergence, slow convergence speed are also very obvious. In order to further improve the optimization capability of GA, some improvements have been introduced into GA. Giftson Samuel *et al.* [4] proposed a hybrid particle swarm optimization based genetic algorithm for long-term generator maintenance scheduling. Jiang *et al.* [5] presented an adaptive multi-objective immune genetic algorithm with vaccine injection for the optimization of cognitive ration waveform. Li *et al.* [6] presented a hybrid simulated annealing and genetic algorithm for optimizing arterial signal timings under oversaturated traffic conditions.

Biological immune system (BIS) is a complicated distributed adaptively learning system, and it has various interesting features such as immunologic defense, tolerance, memory, surveillance and so on. In recent years, the BIS is also introduced into the GA to improve its optimization capability [7]. Ge *et al.* [8][9] proposed an immune genetic algorithm (IGA) through introducing the information entropy and the optimization results of multi-modal function optimization show that the optimization capabilities of IGA are stronger than those of GA. Then, a large number of improved immune genetic algorithms are proposed and applied to engineering optimization. Jiang *et al.* [10] realized the image enhancement based on adaptive immune genetic algorithm. Yin *et al.* [11] finished the distribution network reconfiguration with different distributed generation based on immune genetic algorithm. Luo *et al*. [12] realized the optimal tuning of PI controller for full-order flux observer of induction motor based on the immune genetic algorithm.

The manipulator plays an important role in the industrial production. The different structure sizes of the manipulator will result in the differences at power consumption and dynamic performance. In order to reduce unnecessary motion of the robot joints during the handling and improve the running efficiency of the whole system, the structural optimization design has been the focus of robotic research. Shen *et al*. [13] presented a new virus evolutionary immune clonal algorithm through introducing virus co-evolutionary principles on the

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basis of immune clonal algorithm and realized the optimization of manipulator. In this paper, based on the optimization model of the manipulator in [12], the improved immune genetic algorithm [8] [9] is introduced to finished the optimization of the manipulator.

II. Description of Manipulator Optimization

For the manipulator of translation low loader (see Fig.1), it can be converted into motion sketch as shown in Fig.2 [13].

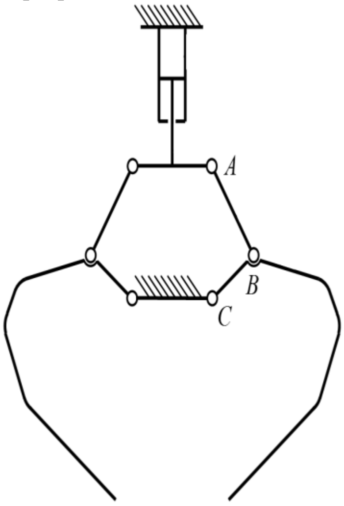


Fig.1 Motion schematic of the manipulator

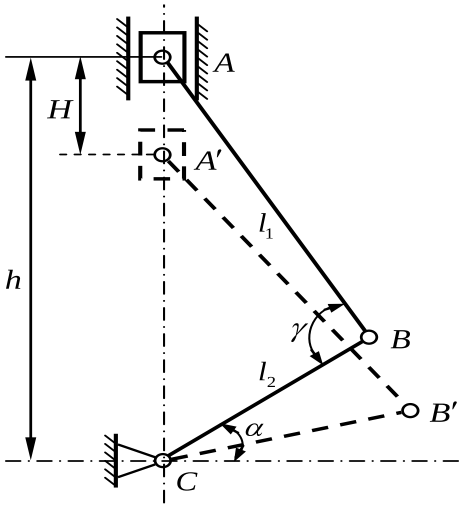


Fig.2 Motion sketch of the manipulator

The lengths l_1, l_2 and h are taken as the design variables, namely, $\boldsymbol{x}=[x_1, x_2, x_3]^T = [l_1, l_2, l_3]^T$. The objective function can be described as:

$$\min f(\boldsymbol{x}) = \frac{x_1^2 + x_2^2 - x_3^2}{2x_1x_2} \tag{1}$$

The constraint conditions are:

$$\begin{cases} g_1(\boldsymbol{x}) = 0.707 + \dfrac{x_1^2 + x_2^2 - x_3^2}{2x_1x_2} \geq 0 \\ g_2(\boldsymbol{x}) = 0.707 - \dfrac{x_1^2 + x_2^2 - x_3^2}{2x_1x_2} \geq 0 \\ g_3(\boldsymbol{x}) = \sin^{-1}\left[\dfrac{x_1^2 + x_2^2 - x_3^2}{2x_1x_2}\right] + \dfrac{\pi}{18} \geq 0 \\ g_4(\boldsymbol{x}) = \dfrac{\pi}{6} - \sin^{-1}\left[\dfrac{x_1^2 + x_2^2 - x_3^2}{2x_1x_2}\right] \geq 0 \end{cases} \tag{2}$$

The boundary conditions are:

$$\begin{cases} g_5(x) = x_1 - 85 \geq 0 \\ g_6(x) = 150 - x_1 \geq 0 \\ g_7(x) = x_2 - 100 \geq 0 \\ g_8(x) = 200 - x_2 \geq 0 \\ g_9(x) = x_3 - 70 \geq 0 \\ g_{10}(x) = 150 - x_3 \geq 0 \end{cases} \tag{3}$$

III. Improved Immune Genetic Algorithm[8][9]

Compared with the genetic algorithm, the immune genetic algorithm adds the calculation of concentration based on the information entropy.

3.1 Information entropy of population [14]

Suppose that the population of artificial immune system consists of N antibodies, and each antibody has L genes, on the basis of the theory of information entropy, the entropy at j^{th} position of N antibodies can be described:

$$H_j(N) = \sum_{i=0}^{1} -p_{ij} \log_{10} p_{ij} \tag{4}$$

$$p_{ij} = \frac{\text{Total number of symbol } i \text{ at } j^{\text{th}} \text{ position of } N \text{ antibodies}}{N}$$

The average information entropy of the whole population is:

$$H(N) = \frac{1}{L}\sum_{j=1}^{L} H_j(N) \tag{5}$$

3.2 Calculation of the expected reproduction rate

The similarity between antibody $\boldsymbol{x}$ and $\boldsymbol{y}$ can be described:

$$A_{ij} = \frac{1}{1+H(2)} \tag{6}$$

Where $H(2)$ can be obtained through equations (4) and (5) when N=2.

The concentration of antibody $\boldsymbol{x}$ is defined as

$$D_x = \frac{1}{N}\sum_{j=i}^{N} Q_{ij} \tag{7}$$

Where

$$Q_{ij} = \begin{cases} 1 & A_{ij} > \gamma \\ 0 & otherwise \end{cases} \tag{8}$$

and γ is the preset threshold value of the similarity.

The affinity between antigen and antibody [8, 9] is defined as:

$$Af_x = Fit(\boldsymbol{x}) + Pra(\boldsymbol{x}) \tag{9}$$

Where, Fit($\boldsymbol{x}$) is the fitness of antibody $\boldsymbol{x}$. $Pra(\boldsymbol{x})$ is the excitation value of an antibody which is next to the local or global optimal points.

The expected reproduction rate (Err) of antibody $\boldsymbol{x}$ can be described as:

$$E\text{rr}(\boldsymbol{x}) = \frac{Af_x}{D_x} \tag{10}$$

3.3 Flow of the improved immune genetic algorithm

Step1. Initialize algorithm parameters: antibody size N of operation population $\boldsymbol{S}$, antibody size M of memory population $\boldsymbol{R}$, selection probability P_s, crossover probability P_c, mutation probability P_m, threshold value γ, maximal evolutionary generation $k_{\max}$, and so on. $k \leftarrow 0$.

Step2. Generate initial operation population $\boldsymbol{S}(k)$ and memory population $\boldsymbol{R}(k)$.

Step3. Calculate the expected reproduction rates Errs of all antibodies in $\boldsymbol{S}(k)$.

Step4. Execute selection operation T^s aiming at $\boldsymbol{S}(k)$ based on P_s: $\boldsymbol{S}'(k) \leftarrow T^s(\boldsymbol{S}(k))$.

Step5. Execute crossover operation T^c aiming at $\boldsymbol{S}'(k)$ based on P_c: $\boldsymbol{S}''(k) \leftarrow T^c(\boldsymbol{S}'(k))$.

Step6. Execute mutation operation T^m aiming at $\boldsymbol{S}''(k)$ based on P_m: $\boldsymbol{S}'''(k) \leftarrow T^m(\boldsymbol{S}''(k))$.

Step7. $\boldsymbol{S}(k) \leftarrow \boldsymbol{S}'''(k)$. Calculate the expected reproduction rates Errs of all antibodies in $\boldsymbol{S}(k)$ and $\boldsymbol{R}(k)$.

Step8. Select N better antibodies as the individuals of $\boldsymbol{S}(k)$ and M better antibodies as the individuals of $\boldsymbol{R}(k)$.

Step9. Judge whether the terminating condition is satisfied. If not, $k \leftarrow k+1$, go to Step 4, otherwise end.

IV. Function Optimization Test and Analysis

In order to verify the optimization performance of the improved immune genetic algorithm (IIGA), the following five functions are provided to test on a computer by using Matlab. The test results are compared with those of the GA. In IIGA, N=30, M=10, P_s=0.08, P_c=0.6, Pm=0.2, K_{max}=150. In GA, N=30, P_s=0.08, P_c=0.3, P_m=0.1, K_{max}=100. Considering the randomness of intelligent algorithms, each function was independently tested with 30 repetitions.

1. Bohachevsky function

$$\min f_1 = x_1^2 + x_2^2 - 0.3\times\cos(3\pi x_1) + 0.3\times\cos(4\pi x_2) + 0.3 \tag{11}$$

$x_i \in$ [-1,1], $1\leq i \leq 2$, f^*= 0.

2. Ackley's Path function

$$\min f_2 = -20\exp(-0.2sqrt(0.5(x_1^2 + x_2^2))) - \exp(0.5(\cos(2\pi x_1) + \cos(2\pi x_2))) + \exp(1) + 20 \tag{12}$$

$x_i \in$ [-5.12,5.12], $1\leq i \leq 2$, f^*= 0.

3. Six-hump camel back function

$$\min f_3 = (4 - 2.1x_1^2 + x_1^4/3)\times x_1^2 + x_1x_2 + (-4 + 4x_2^2)\times x_2^2 \tag{13}$$

$x_1 \in$ [-3, 3], $x_2 \in$ [-2, 2], $1\leq i \leq 2$, f^*= -1.0316.

4. Needle-in-a-haystack function

$$\min f_4 = -\left(\left(\frac{3}{0.05 + x_1^2 + x_2^2}\right)^2 + (x_1^2 + x_2^2)^2\right) \tag{14}$$

$x_i \in$ [-5.12, 5.12], $1\leq i \leq 2$, f^*= -3600.

5. Schaffer's Function

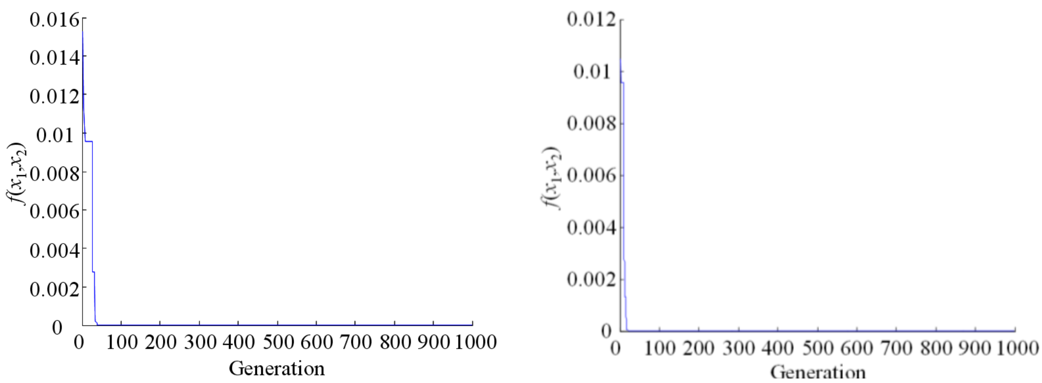
$$\min f_5 = 0.5 + ((\sin(sqrt(x_1^2 + x_2^2)))^2 - 0.5)/((1 + 0.0001(x_1^2 + x_2^2)^2)^2) \tag{15}$$

$x_i \in$[-10, 10], $1\leq i \leq 2$, f^*= 0.

Table 1 Comparison results among three algorithms

f	ε	N_{best}		N_{max}		N_{mean}	
		GA	IIGA	GA	IIGA	GA	IIGA
f_1	1.0E-03	11	14	896	776	648	393
f_2	1.0E-03	26	25	597	545	360	251
f_3	1.0E-03	21	23	860	665	471	304
f_4	1.0E-0	22	25	639	575	227	207
f_5	1.0E-03	23	25	880	809	350	305

Table 1 is the comparison results among GA and IIGA. N_{best} denotes the number of times an optimal solution was found. N_{max} and N_{mean} denote the maximum and average convergence generations needed to find the optimal solutions, respectively. From the comparison results in table 1, we can see that the optimization results of IIGA are better than those of GA, which shows the strong optimization ability of the improved genetic algorithm.



(a) GA (b) IIGA

Fig.3 Average evolutionary curves of Schaffer's function

Fig.3 gives the evolutionary curves of Schaffer's function optimized by GA and IIGA. From the two curves, it can also be seen that the convergence speed of the proposed IIGA is faster than the speed of GA, which further verify the effectiveness of the IIGA.

V. Optimization and Test of Manipulator

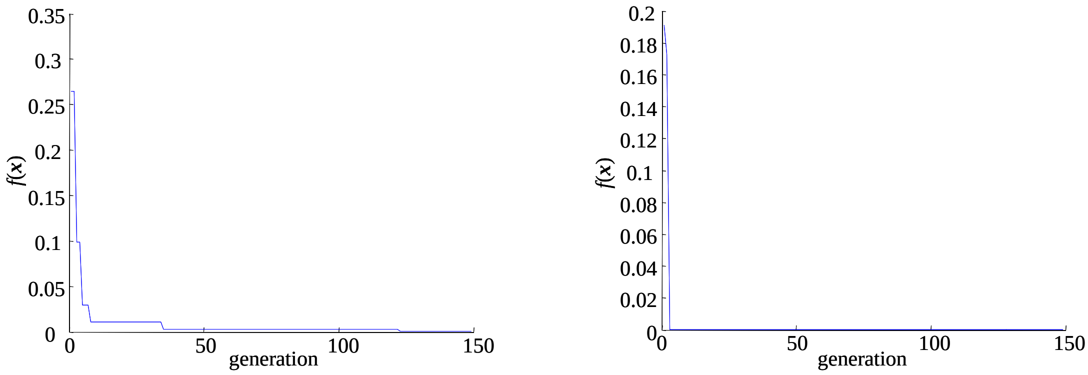
In order to further verify the validity of the improved immune genetic algorithm in the optimization of manipulator, we execute a test. The objective function and constraint conditions are shown in Eqs.(1)-(3). The parameters of IIGA and GA are set as the same in the function optimization.

Table 2 gives the optimization comparison of manipulator among three algorithms, namely, Compound optimization method (COM), GA and the IIGA. From the table, we can see that the optimization results of two intelligent algorithms (namely, GA and IIGA) are better than the result of COM for their global optimization ability. The optimization results of IIGA are better than the results of GA because the information entropy is used to construct the expected reproduction rate of antibody and the antibodies are selected reasonably during the optimization.

Table 2 Comparison results of manipulator among three algorithms

Algorithm		$\min f(\boldsymbol{x})(\times 10^{-5})$	$x_1(l_1)$	$x_2(l_2)$	$x_3(h)$
Compound optimization method		5.66	90.25	108.65	141.24
GA	Average value	3.84	\	\	\
	Optimal solution	2.83	98.58	103.05	142.61
IIGA	Average value	3.37	\	\	\
	Optimal solution	2.28	85.83	120.04	147.57

Fig. 4 gives the evolutionary curves about the whole population of two intelligent optimization algorithms. From the figure, it can be seen that the convergence speed of the IIGA is also faster than the convergence speed of GA, which further verifies the validity of the IIGA in the optimization of manipulator.



(a) GA (b) IIGA

Fig.4 Evolutionary curves about the whole population

VI. Conclusion

In order to solve the optimization of the rolling transport mechanism of manipulator, on the basis of the simple genetic algorithm, an improved immune genetic algorithm is stated. In the improved immune genetic algorithm, the information entropy is introduced to define the antibody concentration firstly, and then the expected reproduction rate of antibody is constructed. Based on the expected reproduction rate, the antibodies can be selected reasonably during the optimization and the optimization ability of GA is improved greatly. The optimization results of the typical function test and the manipulator optimization verify the effectiveness of the IIGA.

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