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Research on The Influence of Earnings Information Quality on the Investment Behavior of Enterprises

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Abstract

Cat swarm optimization algorithm has some disadvantages, such as poor global searching ability and severe randomness; in order to overcome the disadvantages, this article puts forward the immune the immune cat swarm algorithm which firstly randomly picks out a large number of "cat" individuals according to the given space and computes the fitness of each "cat", then assesses the immune factor probability concentration of all "cats", and at last, update the position of individual "cat" according to the concentration difference. Based on the concept of Cat Swarm Optimization, the new algorithm introduces the idea of global optimal value to enhance the global search capability; meanwhile, the sociability of the "cat" is strengthened while keeping the diversity of the "cat", so that the search accuracy is improved and convergence speed is accelerated. Comparison tests for the improved algorithm, basic particle swarm and basic cat swarm are conducted on the 5 testing functions, and the computation results show that the new algorithm has faster convergence speed and higher search accuracy. At the same time, the new algorithm can be used the optimization computation of investment income, so as to determine the optimal value of investment income and obtain the best cost-benefit ratio.

Keywords: *Cat swarm optimization; Immune; Global search; Investment income*

1. Introduction

"Cat" Swarm Optimization algorithm (CSO) is a bionic evolutionary algorithm which simulates cat searching [1]. As a new evolutionary algorithm, "Cat" Swarm Algorithm is different from the real cat in real world, but bases on the basic characteristics of the cat and combines the ideas of swarm intelligent algorithms like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). Compared with the PSO algorithm, the CSO algorithm has stronger local search capability, and the "cat" in search state can be used to increase the randomness, and in search of the state of the "cat" can be used to increase the randomness, and meanwhile the disadvantage of PSO algorithm being easy to get trapped in local optimal values can be avoided. Cat Swarm Optimization algorithm has the problem of higher local search randomness, which limits the algorithm accuracy. As it does not adopt the global search mode, the convergence speed is comparatively slow. This article introduces the immune factors and the selection method of immune factor concentration, which reduces the problem of random selection of the "cat" in chaos algorithm and improves the search accuracy.

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2. Immune Cat Swarm Optimization

2.1. Basic CSO

CSO algorithm is a random optimization method, which initially generate a group of random "cats", and then find the optimal solution through iteration. In the process of each iteration, the "cats" are updated by means of tracking and search. The "cat" in the algorithm use the following formula to update its speed and new position:

$$V^d(t+1) = V^d(t) + C \times Random \times \left[P^d_{best}(t) - P^d(t)\right] \tag{1}$$

$$P_{i,j}(t+1) = P_{i,j}(t) + P_{i,j}(t) \times (SRD * (Random * 2 - 1)) \tag{2}$$

$P_{i,j}$ is the current position, P^d_{best} is the optimal value of current position. SRD is the variation coefficient; V^d is the speed of Cat No. *d*.

(1) is the tracking mode, and the speed position is updated in accordance with the current optimal position; (2) is the search mode, which is similar to the variation operation in genetic algorithm and can reduce the probability of being trapped in local optimal values.

2.2. Immune Factors

Biological immune system is a necessary defense system for creatures in nature, and it is composed of tissues, organs and cells, *etc.*, that having immune functions, and it protects the biological organism from against pathogens. The immune function of biological immune system is realized through the self-adjustment function of lymphocytes. In the immune system, there are mainly two types of lymph cells. The main function of cells is to produce antibodies, and the cells mainly realize the immune regulating function. In terms of biological information processing, the immune system has the following characteristics: Diversity: Diversity is one of the important features of the immune system; according to the immunological preliminary researches, through the cell division and differentiation, somatic hyper-mutation, gene recombination of antibody variable region and constant region and other methods, the immune system can generate a large amount of different antibodies against various antigens, so that the immune antibody library is characterized by diversity. Immune homeostasis: The immune system has a mechanism to maintain immune balance, and this mechanism can limit the strength of immune response within a certain level. By means of inhibiting and promoting the antibodies, the homeostasis mechanism can generate appropriate amount of necessary antibodies.

In the CSO algorithm, the concentration of any "cat" is defined as:

$$C(x_i) = \frac{1}{\sum_{i=1}^{N} f(x_i) - f(x_j)}, ? \neq j \tag{3}$$

(3)In Formula (3), $f(x_i)$ represents the fitness of any "cat" in the computation swarm;

$$PRO\left(x_i\right) = \frac{\frac{1}{C\left(x_i\right)}}{\frac{1}{\sum_{i=1}^{N} C\left(x_i\right)}} \tag{4}$$

(4)In Formula (4), $PRO(x_i)$ is the probability of antibody; the more the number of antibodies corresponding to certain individual is, the smaller the probability of this individual being selected will be. Conversely, the less the number of antibodies corresponding to certain individual, the bigger the probability of this individual being selected will be. This makes it possible for low fitness individuals getting the opportunities of evolution. Therefore, the probability selection formula that is based on antibody concentration ensures the diversity of antibodies in theory. Select the "cat" individuals according to Step 5-8 of the algorithm put forward in Reference [6].

The steps of Immune Cat Swarm Optimization algorithm are as follows:

Table 1. Immune Factors Chaos CSO Algorithm Steps

Steps	Algorithm Operation
Step1	Generate random "cat" swarm and speed according to the given search space
Step 2	Compute the fitness according to the target function and generated "cats"
Step 3:	Calculate the global optimal value
Step 4	Compute the antibody concentration and its probability of all "cats" in the swarm according to Formula (3) and (4)
Step 5	Change the positions and speeds of the "cats" according to the speed and position updating formula
Step 6	Select the "cats" according to the computation results and Reference [6]
Step 7	Evaluate the search mode, if the tracking mode is met, continue operation to Step 8, and if not, skip to Step 9
Step 8	Carry out the tracking search by the selected "cats"
Step 9	Carry out the search mode
Step 10	Compute the fitness of all individuals and keep the optimal solution
Step 11	Determine whether the biggest evolution algebra is met, if not, skip to Step 4; if it is met, skip to Step 10
Step 12	Output the global optimal values and global optimal variable values

3. Comparison Test

3.1. Test Function and Environment

The latest six test functions are selected as the test functions [7-8], and the testing environment is : Matlab R2009, Windows XP. The hardware include Core i3 3.3 GHz, 2GB DDR3 1.6GHz.

Select the test functions according to Reference [7] to [9], and the test functions are listed in the table below:

Table 2. Test Functions

Functions	Formula
F_1	$(x_1+2x_2-7)^2+(2x_1+x_2-5)^2$
F_2	$100(x_1^2-x_2)^2+(x_1-1)^2+(x_3-1)^2$ $+90(x_3^2-x_4)^2+10.1\left[(x_2-1)^2+(x_4-1)^2\right]+$ $19.8(x_2-1)(x_4-1)$
F_3	$-\cos(x_1)\cos(x_2)e^{[-(x_1-\pi)^2-(x_2-\pi)^2]}$
F_4	$4x_1^2-2.1x_1^4+\frac{1}{3}x_1^6+$ $x_1x_2-4x_2^2+4x_1^4$
F_5	$0.26(x_1^2+x_2^2)-0.48x_1x_2$

SPSO, CSO and IMCSO are selected for the comparison test. SPSO has a good accuracy and convergence speed, and is widely used and improved. Through the comparisons with another two different algorithms, it can be proved that the asynchronous learning factor can regulate the "cat's" sociality and their own learning performance.

The search ranges of test functions are shown in the table below:

Table 3. Search Range of Test Functions

Functions	Search Range
F_1	[-10,10]
F_2	[-10,10]
F_3	[-10,10]
F_4	[-5,5]
F_5	[-10,10]

According to the search range of Table 3, the position of the swarm can be randomly initialized within specified range.

3.2. Test Results

Table 4. Comparison of Search Accuracy

Test functions	SPSO	CSO	IMCSO
F_1	3.98e-05	1.98e-08	1.51e-11
F_2	2.74e-09	9.91e-19	1.93e-25
F_3	5.14e-08	5.12e-15	2.83e-17
F_4	7.03e-08	2.82e-11	4.24e-13
F_5	9.35e-03	4.07e-06	4.01e-08

According to the results of test comparison, IMCSO has the highest search accuracy on the five functions, and SPSO has the lowest accuracy; the search accuracy of CSO is higher than that of SPSO. In the 1st, 2nd and 3rd functions, IMCSO has higher accuracies, which means immune factors and immune selection can improve the search accuracy.

Table 5. Comparison of Search Time

Test functions	Given Accuracy	SPSO	CSO	IMCSO
F_1	0.01	24.5645s	20.9515s	21.7993s
F_2	0.01	38.6721s	37.3134s	37.2881s
F_3	0.01	23.8732s	19.7439s	22.7934s
F_4	0.01	19.0073s	18.0709s	15.2512s
F_5	0.01	8.8732s	6.3783s	10.3170s

It can be seen from Table 5, that the shortest time for basic CSO algorithm reaching the given accuracy appears on the 1st, 3rd and 5th functions; the shortest time for immune CSO algorithm reaching specified accuracy appears on the 2nd and 4th functions, and the main reason is that the computation of immune factor probability and selection increases the operation time of the algorithm.

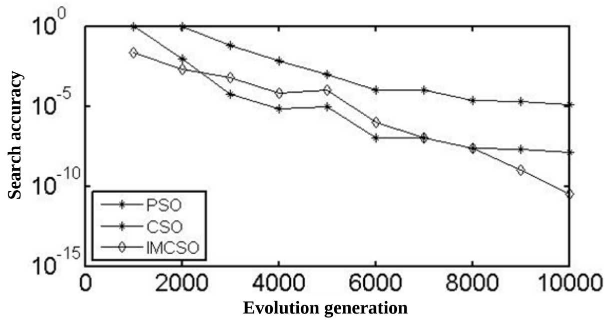

Figure 1. High Search Accuracies in Test Function

Three algorithms all show high search accuracies in test function F1; the evolution speeds of PSO and CSO in later evolution period after 6000 times begin to slow down obviously, however, IMCSO expands the diversity of the swarm on the basis of immune selection, making it still have large potential in later period.

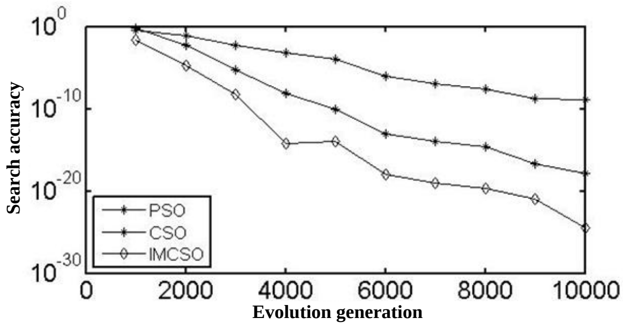

Figure 2. Test Results of the Two Algorithms in F2

As shown in Figure 2, three algorithms have similar accuracies at circles about 1000 times, but their immune selection performance vary with the increasing of circle times; after circle times increasing to 4000 times, the convergence speed of IMCSO continuously accelerates.

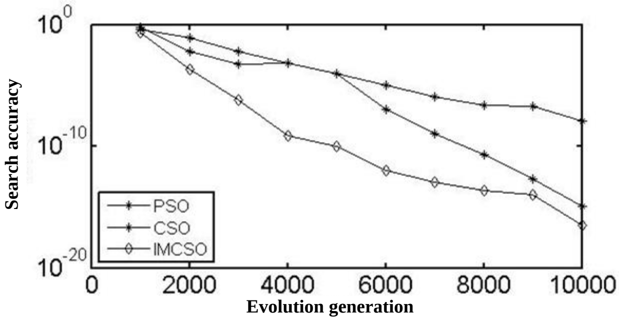

Figure 3. Test Results of Two Algorithms on F3

In Figure 3, IMCSO has the highest accuracy; CSO runs into oscillation at 5000 circle times, which is caused by the random variance in search mode and the trigonometric function in test function; both IMCSO and CSO have much higher accuracies than that of SPSO.

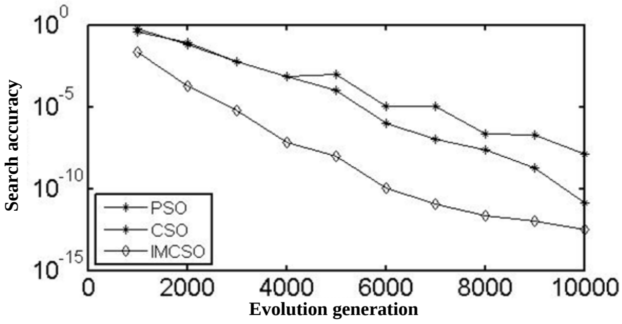

Figure 4. Test Results of the Two Algorithms in F4

In Figure 4, the convergence process of SPSO runs into obvious stagnation while the convergence speeds of CSO and IMCSO are both very fast, and the accuracy of IMCSO is higher than those of SPSO and CSO.

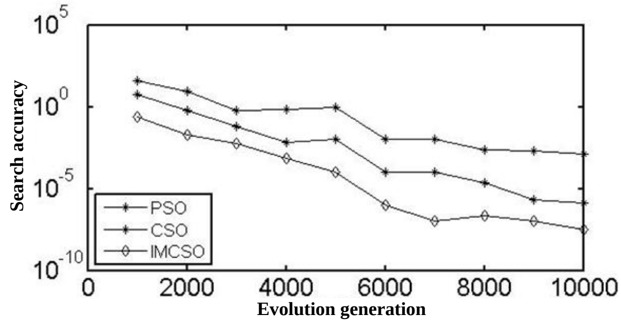

Figure 5. Test Results of the Two Algorithms in F5

The new algorithm IMCSO has a higher accuracy in the fifth function than that of SPSO. The new algorithm has a slightly higher search accuracy than that of CSO. The convergence speed of IMCSO begins to slow down after 6000 cycle times.

3.3. Actual Application

Mean variance portfolio model has the assumptions that margin trading-short and risk-free borrowing are prohibited, and it explores the efficient boundary problem in investment portfolio based on the mean and variance of individual stock returns in asset portfolio, *i.e.*, finding the investment portfolio with the minimum variance in certain returns level, and everywhere investors select investment portfolio only on the efficient boundary [9]. In 2012, the mean ROAs of Shanghai Volkswagen, Shanghai Gm and GTMC are 0.12, 0.09 and 0.06, respectively. The covariance of the relationship among three assets is [12]:

$$H=\begin{matrix} 0.2 & 0.3 & -0.01 \\ 0.3 & 2.4 & 0.5 \\ -0.01 & 0.5 & 1.1 \end{matrix}$$

In order to get the minimum risk portfolio and control the expected returns to 0.1, the following optimization model can be obtained:

$$\min S = [x_1\ x_2\ x_3] \cdot H \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \tag{5}$$

$$\begin{cases} 0.06x_1 + 0.12x_2 + 0.09x_2 = 0.1 \\ x_1 + x_2 + x_3 = 1 \\ x_1, x_2, x_3 > 0 \end{cases} \tag{6}$$

The minimum risk portfolio model is a parameter in optimization (5), and meanwhile it needs to meet the constraint conditions in (6).

The problem is converted into solving the optimal values of three variables with constraint functions, and IMCSO is used for the solution. In order to further analyze and find out the performance, the solution result is compared with IMCSO.

The nominal value is:

Table 6. Nominal Value of Stock Investment Proportion

Company Name	SVW	SGM	GTMC
Investment proportion	46.34%	43.50%	10.16%

Respectively use SPSO, CSO and IMCSO to solve (5) and (6); the solutions obtained are as follows:

Table 7. SPSO Computation Results

Company Name	SVW	SGM	GTMC
Investment proportion	49.84%	40.43%	9.73%

Table 8. CSO Computation Results

Company Name	SVW	SGM	GTMC
Investment proportion	47.44%	43.43%	9.13%

Table 9. IMCSO Computation Results

Company Name	SVW	SGM	GTMC
Investment proportion	46.39%	43.58%	10.03%

By means of solving the relative error, the performances of the optimal investment portfolio models of the three algorithms are verified:

Table 10. Relative Error of Computations of the Three Algorithms

Algorithm	SVW	SGM	GTMC
SPSO	7.62%	7.06%	4.23%
CSO	2.46%	0.16%	10.14%
IMCSO	0.09%	0.18%	1.28%

It can be seen from Table 10 that, IMCSO has a higher search accuracy, which means IMCSO is more suitable for solving the multi-variable combinational optimization problems.

4. Conclusion

This article puts forward a new immune cat swarm optimization algorithm. This algorithm is based on the concept of immune factor concentration, and screen the antigens according to the antibodies in immune factors; while keeping the "cats" with high fitness, it improves the sociability of each "cat" and keeps the diversity of the "cats", and meanwhile, it improves the global search capability and search accuracy of the "cat" swarm. The slightly high time complexity is a disadvantage of this algorithm. Further research will focus on how to maintain the diversity of the individuals as well as higher search accuracy of IMCSO, and meanwhile reduce the time complexity. At the same time, the example proves the high application value of IMCSO, showing that it can solve the optimal allocation problem in financial investment.

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References

[1] W. Gu, Z. Lv and M. Hao, “Change detection method for remote sensing images based on an improved Markov random field”, Multimedia Tools and Applications, **(2016)**.

[2] Z. Lu, C. Esteve, J. Chirivella and P. Gagliardo, “A Game Based Assistive Tool for Rehabilitation of Dysphonic Patients”, 3rd International Workshop on Virtual and Augmented Assistive Technology (VAAT) at IEEE Virtual Reality 2015 (VR2015), Arles, France, IEEE, **(2015)**.

[3] Z. Lv, A. Halawani, S. Feng, H. Li and S. U. Rehman, “Multimodal Hand and Foot Gesture Interaction for Handheld Devices”, ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), vol. 11, no.1, Article 10 (**2014**) October, pp.19.

[4] Y. Lin, J. Yang, Z. Lv, W. Wei and H. Song, “A Self-Assessment Stereo Capture Model Applicable to the Internet of Things”, Sensors, **(2015)**.

[5] W. Ou, Z. Lv and Z. Xie, “Spatially Regularized Latent topic Model for Simultaneous object discovery and segmentation”, The 2015 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (**2015**).

[6] Y. Wang, Y. Su and G. Agrawal, “A Novel Approach for Approximate Aggregations Over Arrays”, In Proceedings of the 27th international conference on scientific and statistical database management, ACM, **(2015)**.

[7] Z. Lv, A. Halawani, S. Feng, S. U. Rehman and H. Li, “Touch-less Interactive Augmented Reality Game on Vision Based Wearable Device”, Personal and Ubiquitous Computing, **(2015)**.

[8] Z. Lv, X. Li and B. Zhang, “Managing Big City Information Based on WebVRGIS”, IEEE Access, vol. 4, **(2016)**, pp. 407-415.

[9] J. Yang, Y. Lin and Z. Gao, “Quality Index for Stereoscopic Images by Separately Evaluating Adding and Subtracting”, PloS one, vol. 10, no. 12, **(2015)**, pp. e0145800.

[10] D. Jiang, Z. Xu and Z. Lv, “A multicast delivery approach with minimum energy consumption for wireless multi-hop networks”, Telecommunication Systems, **(2015)**, pp. 1-12.

[11] Y. Liu, J. Yang and Q. Meng, “Stereoscopic image quality assessment method based on binocular combination saliency model”, Signal Processing, vol. 125, **(2016)**, pp. 237-248.

[12] Z. Lv, A. Tek and F. Da Silva, "Game on, science-how video game technology may help biologists tackle visualization challenges", PloS one, vol. 8, no. 3, **(2013)**, pp. e57990.
[13] X. Zhang, Y. Han, D. Hao and Z. Lv, "ARPPS：Augmented Reality Pipeline Prospect System", 22th International Conference on Neural Information Processing, Istanbul, Turkey. In press. (ICONIP) (**2015**)

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