Improved Cuckoo Search Algorithm with Novel Searching Mechanism for Solving Unconstrained Function Optimization Problem

Shu-Xia Li, and Jie-Sheng Wang

***Abstract*—Cuckoo search (CS) algorithm is a new biological heuristic algorithm and simulates the cuckoo's seeking nest and spawning behavior and introduces levy flight mechanism. In order to improve the convergence velocity and optimization accuracy of cuckoo search algorithm, by combining the learning-evolving thought with Gaussian distribution, a new searching mechanism that with a learning-evolving searching guider is proposed. Then combining the new searching mechanism proposed with the Levy Flight searching mechanism according to a selection probability, a new searching mechanism cuckoo search (MCS) algorithm is formed. The result of functions testing under different dimensions proves the superiority of new proposed MCS algorithm.**

***Index Terms*—cuckoo search algorithm, function optimization, searching mechanism, Gaussian distribution**

I. Introduction

CUCKOO search (CS) algorithm is put forward by Yang and Deb in 2009, which simulates the cuckoo's seeking nest and spawning behavior and introduces levy flight mechanism into it, which is able to quickly and efficiently find the optimal solution [1-2]. This algorithm is mainly based on two aspects: the cuckoo's parasitic reproduction mechanism and Levy flights search principle. In nature, cuckoos use a random manner or a quasi-random manner to seek bird's nest location. Most of cuckoos lay their eggs in other bird nests and let the host raise their cubs instead of them. If a host found that the eggs are not its owns, it will either throw these alien eggs away from the nest or abandon its nest and build a new nest in other places. However, there are some cuckoos choosing nest that the color and shape of the host's egg are similar with their owns to win the host's love, which can reduce the possibility of their eggs being abandoned and increase the reproduction rate of the cuckoos. Studies have proved that CS algorithm are better than other swarm intelligence algorithms in convergence rate and optimization accuracy, such as ant colony optimization (ACO) algorithm [3], genetic algorithm (GA) [4], bat algorithm (BA) [5], artificial bee colony (ABC) algorithm [6], etc. In that this algorithm has the characteristics of fewer parameters, simple and easy to implement, now it has been successfully applied in a variety of engineering optimization problems and has a very high potential research value [7-8].

Cuckoo algorithm is mainly based on two aspects: the cuckoo's nest parasitic reproductive mechanism and Levy flights search principle. In nature, cuckoos use a random manner or a quasi-random manner to seek bird's nest location [9-10]. However, some cuckoos choose nest that the color and shape of the host's eggs are similar with their owns to win the host's love. The paper is organized as follows. In section 2, the improved cuckoo search algorithm with the novel searching mechanism for solving unconstrained function optimization problem is introduced. The simulation experiments and results analysis are introduced in details in section 3. The conclusion illustrates the last part.

II. Improved Cuckoo Search Algorithm with Novel Searching Mechanism

A. Basic Cuckoo Search Algorithm

In general, each cuckoo can only lays one egg, and each egg on behalf of one solution (cuckoo). The purpose is to make the new and potentially better solutions replace the not-so-good solutions (cuckoos). In order to study the cuckoo search algorithm better, the simplest method is adopted, that is to say only one egg is in each nest. In this case, an egg, a bird's nest or a cuckoo is no differences, which is to say each nest corresponding to a cuckoo's egg. For simplicity in describing the cuckoo search algorithm, Yang and Deb use the following three idealized rules to construct the cuckoo algorithm [11-12].

(1) Each cuckoo only lays one egg at a time, and randomly choose bird's nest to hatch the egg.

(2) The best nest will carry over to the next generation.

(3) The number of available host nests is fixed, and the probability of a host discovers an alien egg is $P_a = [0,1]$.

Cuckoo algorithm is based on random walk of Levy flight

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making search. Levy flight is a random walk, whose step size obeys Levy distribution, and the direction of travel is subject to uniform distribution. On the basis of these rules, updating formula of the cuckoo nest location is described as follows:

$$x_i^{(t+1)} = x_i^t + \alpha s_L \tag{1}$$

$$S_L = levy(\lambda) \tag{2}$$

where, x_i^t represents the position of the i -th nest at the t -th generation, x_i^{t+1} represents the position of the i -th nest at the $(t+1)$ -th generation ; α is step control volume; $levy(\lambda)$ is a vector obeying Levy distribution:

$$L(s,\lambda) = \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}},(s \gg s_0) \tag{3}$$

where, $s_0 > 0$ represents the minimum step, Γ is a gamma function; the step of $levy(\lambda)$ obeys levy distribution. In general, levy distribution is usually expressed as follows:

$$L(\beta,\lambda) = \frac{1}{\pi}\int_0^\infty \cos(ks)\exp[-\beta|k|^\lambda]dk \tag{4}$$

In the Eq. (4), there is no any form of explicit analysis; therefore, it is difficult to obtain a random sample by the formula. But, when $s \gg s_0 > 0$, the Eq. (4) can be approximated as the following equation:

$$L(\beta,\lambda) = \frac{\beta\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi|s|^{1+\lambda}} \tag{5}$$

When $\beta = 1$, the Eq. (5) is equivalent to Eq. (4). Although the Eq. (5) can describe random walk behavior of the cuckoo algorithm, but it is not conducive to the description of the mathematical language, and is more disadvantageous to the writing of the program. So, Yang Xin She and Deb found that in the realization of the CS algorithm adopting Mantegna algorithm can well simulate random walk behavior of levy flight [13]. In this algorithm, the step length s can be represented as:

$$s = \frac{u}{|v|^{1/\lambda}}, 1 \le \lambda \le 2 \tag{6}$$

where s is leap path of levy flying ; Parameters u and v are subject to normal distribution shown as Eq. (7):

$$\mu \sim N(0,\sigma_\mu^2), v \sim N(0,\sigma_v^2) \tag{7}$$

$$\sigma_\mu = \left(\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right)^{1/\beta}, \sigma_v = 1 \tag{8}$$

This algorithm can generate samples approximate to levy distributed. In theory $s_0 \gg 0$, but in practice, s_0 can take a very small value, such as $s_0 = 0.1$.

B. New Search Mechanism Cuckoo Search Algorithm (MCS)

In the basic CS algorithm, step size and the direction generating by using the levy flight search mechanism are highly random. It is known from Eq. (6) that the step size of levy flight completely depends on of the random number u and v, which makes the search have characteristics of great randomness and blindness. And in the search process there is lack of information communication between cuckoos. The search is easy to jump from one region to another region, which leads to a low search accuracy and slow convergence speed. In order to make the search with a directivity and teleology and let the algorithm do search under a guide, inspired by the shuffled frog leaping algorithm (SFLA) and variation thought coming from differential evolution (DE) algorithm, in this article, the worst frog's update strategy of SFLA algorithm and variation idea are introduced into search of bird's nest locations.

In SFLA algorithm, in order to get more food faster, poor frog is influenced by good frog jump to the better frog. Based on SFLA algorithm, in order to make a cuckoo hunt for better bird's nest faster, let it learn from the best cuckoo and improve the capability of communicating information with the best cuckoo. The introduction of variation thought make bird's nest has an ability of self-evolving, which can increase the diversity of bird's nest position, that is to say it can increase the diversity of solutions. For improving the search ability of the algorithm, with learning and evolving as the search wizard, the Gaussian distribution is added to the algorithm. Based on the thoughts above, the new search mechanism is as shown follows.

$$lem(i) = c_1(x_1 - x_{best})G_1 + c_2(x_{r_1} - x_{r_2})G_2 \tag{9}$$

where, x_i is the i -th bird's nest location, x_{best} is the current best location, r_1 and r_2 are random number from (1, n), $r_1 \ne r_2$, n is the number of bird's nest population, x_{r_1} and x_{r_2} are the bird's nest locations corresponded to a random number r_1 and r_2 , G_1 and G_2 obey the Gaussian distribution, c_1 is the learning scale and c_2 is evolution scale.

The values c_1 and c_2 control the learning and evolving ability of cuckoos. If c_1 and c_2 are set fixed values, it can make learning and evolution lack flexibility. In order to make the learning and evolution has a flexibility c_1 and c_2 changing as the following formula:

$$c_1 = (0.5+\beta)/2 \tag{10}$$

$$c_2 = (0.5+\gamma)/2 \tag{11}$$

where, β and γ are random number from [0, 1] and obey uniform distribution

Randomness and strong leap characteristics of Levy flight make the algorithm has stronger global searching ability. If fully use the search mechanism that proposed in this paper and abandon Levy flight search mechanism, it will lost the advantages of high searching ability owned by original algorithm, which will result in the algorithm difficult to jump out of local optimal solution. If fully use the Levy flight search mechanism, it will lead to the algorithm has a low search accuracy and slow convergence speed. Therefore, in order to exert advantages of both search mechanism, combining the new searching mechanism proposed in this paper with the Levy Flight according to a selection probability. It can be express as Eq. (13).

$$S_L = \begin{cases} levy(\lambda) & p < cr \\ lem(i) & p \geq cr \end{cases} \tag{12}$$

where, cr is selectiveprobability that balance the two search mechanism and it is constant, $0 < cr < 1$. And p obeys the uniform distribution $p \in [0,1]$.

When $p < cr$, adopting search mechanism of Levy flight to search bird's nest location of the next generation; When $p \geq cr$, using the search mechanism that proposed by this article to search bird's nest location.

III. Simulation Results

In order to verify search performance of the new search mechanism cuckoo search algorithm (MCS). In this paper, six typical functions are chosen to test algorithm performance; the six functions are shown as Table 1. Experimental parameters: total bird's nest population is $n = 25$, the step length controlled parameter $\alpha = 0.01$. The detection probability Pa =0.25, step length control, the Selection probability $cr = 0.45$, The number of iterations $iter = 500$. For each kind of algorithm, the program runs 50 times independently. Evaluate algorithm performance by statistics of the best value, average value and the worst value of 50 times running, and the convergence curves of functions. The numerical test results are shown in Table 2. Convergence curves of Function f_1 - f_6 is shown as Figure 1.

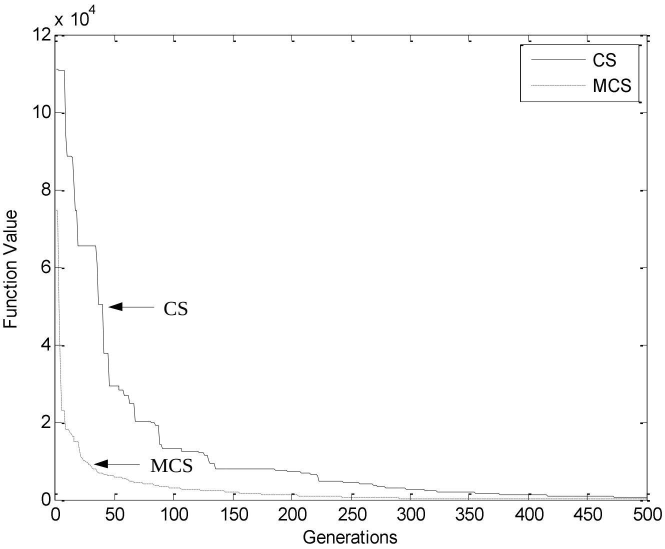
It can be seen from six convergence curves under the different dimensions and numerical results of Table 2 that the MCS algorithm has a higher convergence speed and optimization accuracy than the original CS algorithm. Therefore, MCS algorithm has superior search performance.

TABLE 1. FOUR BENCHMARK FUNCTIONS USED IN THE SIMULATION EXPERIMENTS.

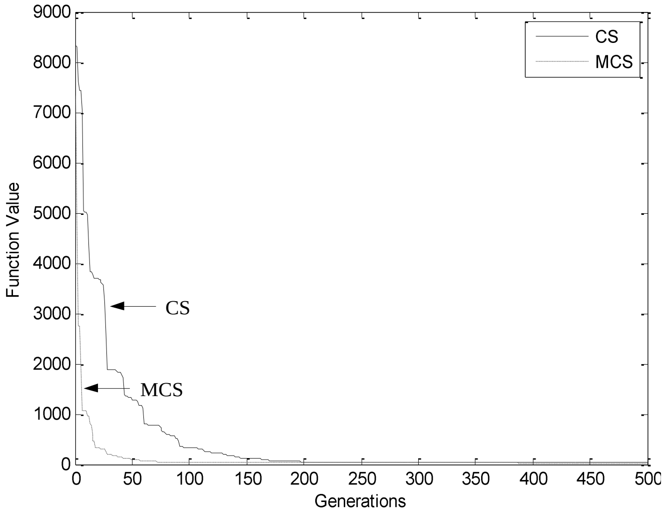
Name	Function	Scope
Sphere	$f_1(\mathrm{x}) = \sum_{i=1}^{d} x_i^2$	[-100,100]
Rosenbrock	$f_2(\mathrm{x}) = \sum_{i=1}^{d-1} (100(\mathrm{x}_{i+1} - \mathrm{x}_i^2) + (\mathrm{x}_i - 1)^2)$	[-2.08,2.08]
Griewank	$f_3(\mathrm{x}) = \frac{1}{4000}\left(\sum_{i=1}^{d}(x^2{}_i)\right) - \left(\prod_{i=1}^{d}\cos(\frac{x_i}{\sqrt{i}})\right) + 1$	[-300,300]
Michalewicz	$f_4(x) = -\sum_{i=1}^{d}\sin(x_i)\left[\sin(\frac{ix_i^2}{\pi})\right]^{2m}, (m=10)$	[0, π]
Rastrigrin	$f_5(\mathrm{x}) = \sum_{i=1}^{d}(\mathrm{x}_i^2 - 10\cos(2\pi\mathrm{x}_i) + 10)$	[-1.25,1.25]
Sumsquares	$f_6(x) = \sum_{i=1}^{d} ix_i^2$	[-10,10]

TABLE 2. COMPARISON OF NUMERICAL TESTING RESULTS

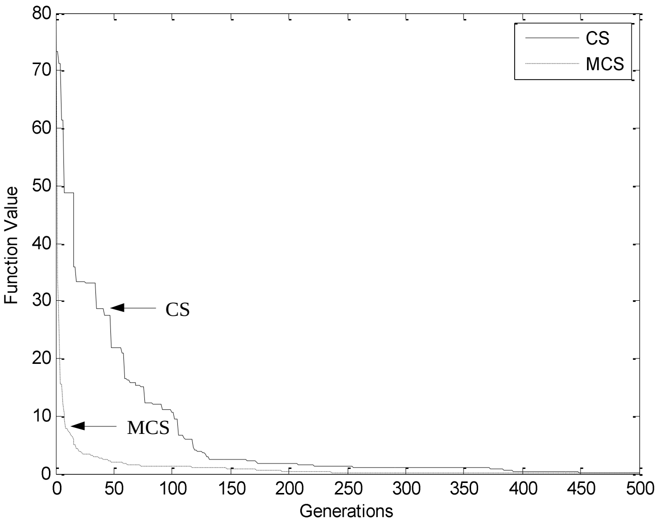
Function	Dim.	Method	Minimum	Maximum	Average
f_1	50	CS	183.9986	707.5202	472.597
		MCS	3.8762	127.8167	26.9362
f_2	30	CS	26.1276	28.5013	27.4316
		MCS	24.1929	29.3975	26.7810
f_3	20	CS	0.0140	0.2893	0.1046
		MCS	2.4732e-009	0.1954	0.0489
f_4	20	CS	-12.5472	-10.1190	-11.1297
		MCS	-14.0290	-10.5290	-13.0131
f_5	10	CS	0.1334	3.0579	2.1498
		MCS	2.8184e-009	2.0284	0.6081
F_6	5	CS	7.1381e-019	9.8367e-016	1.0106e-016
		MCS	2.3139e-046	5.9438e-023	1.2042e-024



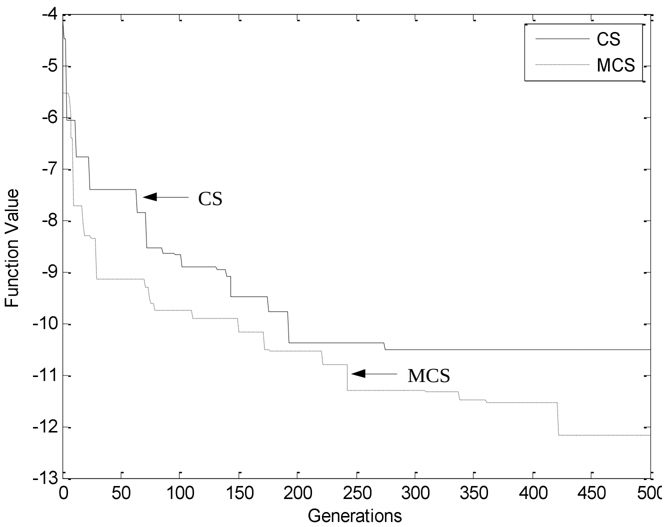
(a) Function f_1



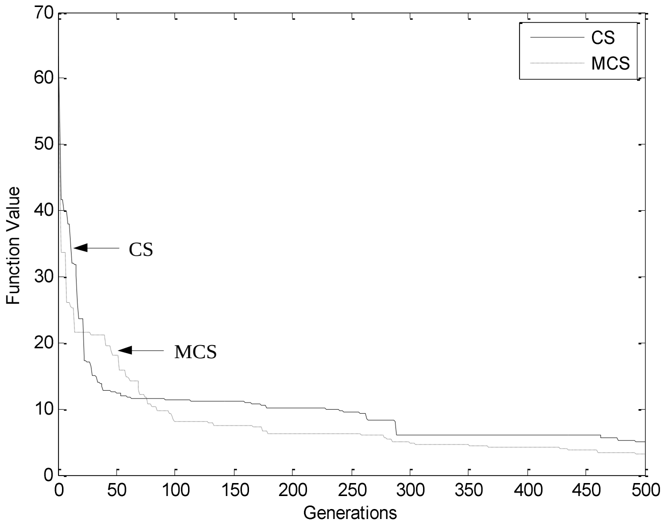
(b) Function f_2



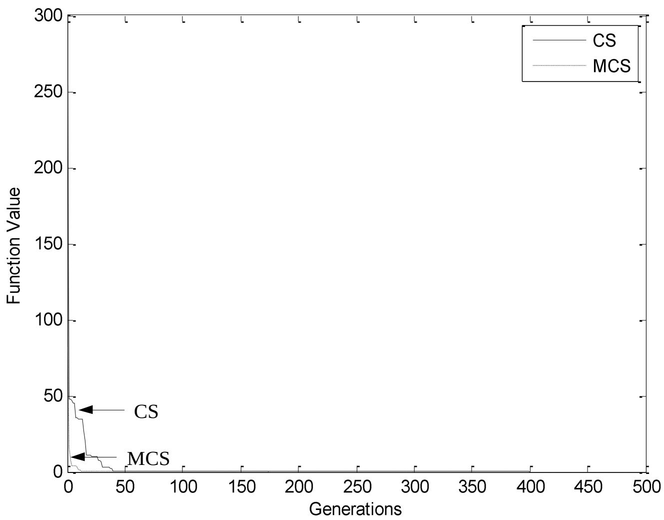
(c) Function f_3



(d) Function f_4



(e) Function f_5



(f) Function f_6

Fig. 1. Convergence curve for six benchmark functions.

IV. Conclusion

This paper proposes an improved cuckoo search algorithm with a novel searching mechanism for solving unconstrained function optimization problem. The simulation results show that the improved cuckoo search algorithm has better convergence velocity and optimization accuracy. In future, this method could be extended to deal with the other optimization problems.

References

[1] X. S. Yang and S. Deb, "Cuckoo search via L´evy flights," *in Proc. World Congress on Nature & Biologically Inspired Computing*, Coimbatore, India, 2009, pp. 210–214.

[2] X. S. Yang and S. Deb, "Engineering optimisation by cuckoo search," *International Journal of Mathematical Modelling and Numerical Optimisation*, vol. 1, no. 4, pp. 330–343, Dec. 2010.

[3] Y. Ghanou, and G. Bencheikh, "Architecture Optimization and Training for the Multilayer Perceptron using Ant System," *IAENG International Journal of Computer Science*, vol. 43, no.1, pp. 20-26, 2016.

[4] E. Vallada, and R. Ruiz, "A genetic algorithm for the unrelated parallel machine scheduling problem with sequence dependent setup times," *European Journal of Operational Research*, vol. 211, no. 3, pp. 612–622, Jun. 2011.

[5] Anping Song, Mingbo Li, Xuehai Ding, Wei Cao, and Ke Pu, "Community Detection Using Discrete Bat Algorithm," *IAENG International Journal of Computer Science*, vol. 43, no.1, pp37-43, 2016.

[6] Chun-Feng Wang, and Yong-Hong Zhang, "An Improved Artificial Bee Colony Algorithm for Solving Optimization Problems," *IAENG International Journal of Computer Science*, vol. 43, no.3, pp336-343, 2016.

[7] X. S. Yang, *Cuckoo search and firefly algorithm*. New York: Springer-Verlag, 2014, pp. 1–26.

[8] E. Valian, S. Mohanna, and S. Tavakoli, "Improved cuckoo search algorithm for feedforward neural network training," *International Journal of Artificial Intelligence & Applications*, vol. 2, no. 3, pp. 36–43, Jul. 2011.

[9] A. H. Gandomi, X. S. Yang, and A. H. Alavi, "Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems," *Engineering with Computers*, vol. 29, no. 1, pp. 17–35, Apr. 2013.

[10] K. Chandrasekaran, and S. P. Simon, "Multi-objective scheduling problem: Hybrid approach using fuzzy assisted cuckoo search algorithm," *Swarm and Evolutionary Computation*, vol. 5, pp. 1–16, Aug. 2012.

[11] X. S. Yang and S. Deb, "Cuckoo search: recent advances and applications," *Neural Computing and Applications*, vol. 24, no. 1, pp. 169–174, Dec. 2014.

[12] A. R. Yildiz, "Cuckoo search algorithm for the selection of optimal machining parameters in milling operations," *The International Journal of Advanced Manufacturing Technology*, vol. 64, no. 1-4, pp. 55–61, Jan. 2013.

[13] P. Civicioglu, and E. Besdok, "A conceptual comparison of the Cuckoo-search, particle swarm optimization, differential evolution and artificial bee colony algorithms," *Artificial Intelligence Review*, vol. 39, no. 4, pp. 315–346, Apr. 2013.

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