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A Novel Cuckoo Search Optimization Algorithm Base on Gauss Distribution ⋆

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Abstract

This paper according to the low convergence of rate of Cuckoo Search (CS) algorithm, a novel cuckoo search optimization algorithm base on Gauss distribution (GCS) is presented. We then apply the GCS algorithm to solve standard test functions and engineering design optimization problems, the optimal solutions obtained by GCS are far better than the best solutions obtained by CS, and the GCS has a high convergence rate.

Keywords: Cuckoo Search; Gauss Distribution; GCS Algorithm

1 Introduction

More and more modern heuristic algorithms inspired by nature are emerging and they become increasingly popular. For example, Particles Swarm Optimization (PSO) was inspired by fish and bird swarm intelligence, while the Firefly Algorithm was inspired by the flashing pattern of tropical fireflies [1, 2, 3, 7, 8]. These nature inspired heuristic algorithms have been used in a wide range of optimization problems, including NP-hard problems such as the travel salesman problem [1, 2, 3, 4, 5, 7]. The power of almost all modern heuristics comes from the fact that they imitate the best feature in nature, especially biological systems evolved from natural selection over millions of years. Two important characteristics are selection of the fittest and adaptation to the environment. Numerically speaking, these can be translated into two crucial characteristics of the modern heuristics: intensification and diversification [2]. Intensification intends to search around the current best solutions and select the best candidates or solutions, while diversification makes sure the algorithm can explore the search space efficiently.

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Recently, a new metaheuristic search algorithm, called Cuckoo Search (CS) [11], has been developed by Yang and Deb (2009). Preliminary studies show that it is very promising and could outperform existing algorithms such as PSO. But, the algorithms later there are slow convergence speed and low accuracy shortcomings. This paper according to the low convergence of rate of cuckoo search algorithm, a novel cuckoo search optimization algorithm base on Gauss distribution (GCS) is presented. We then apply the GCS algorithm to solve standard test functions and engineering design optimization problems, the optimal solutions obtained by GCS are far better than the best solutions obtained by CS.

The remainder of this paper is organized as follows: Section 2 describes the CS optimization algorithm. Section 3 presents a novel GCS algorithm base on Gauss distribution. Standard test functions and engineering design optimization problem discussions are presented in Section 4. Finally, Section 5 provides some conclusions.

2 Cuckoo Search Algorithm

CS is a heuristic search algorithm which has been proposed recently by Yang and Deb [11]. The algorithm is inspired by the reproduction strategy of cuckoos. At the most basic level, cuckoos lay their eggs in the nests of other host birds, which may be of different species. The host bird may discover that the eggs are not it's own and either destroy the egg or abandon the nest all together. This has resulted in the evolution of cuckoo eggs which mimic the eggs of local host birds. To apply this as an optimization tool, Yang and Deb [6] used three ideal rules:

(1) Each cuckoo lays one egg, which represents a set of solution co-ordinates, at a time and dumps it in a random nest;

(2) A fraction of the nests containing the best eggs, or solutions, will carry over to the next generation;

(3) The number of nests is fixed and there is a probability that a host can discover an alien egg. If this happens, the host can either discard the egg or the nest and this result in building a new nest in a new location. Based on these three rules, the basic steps of the Cuckoo Search (CS) can be summarized as the pseudo code shown as follows.

Cuckoo search via Lévy flight algorithm:

begin

  Objective function $f(x), x = (x_1, x_2, ...x_d)^T$

  Generate initial population of n *host nests* $x_i(i = 1, 2, ..., n)$

  While (t <Max Generation) or (stop criterion)

    Get a cuckoo randomly by lévy flight

    Evaluate its quality/fitness F_i

    Choose a nest among n*(say,j)randomly*

    If$(F_i > F_j)$

      replace j *by the new soluton;*

    End

A fraction(p_a) of worse nests are abandoned and new ones are built;
keep the best solutions(or nests with quality solutions);
Rank the solutions and find the current best

End while

Postprocess results and visualization

End

When generating new solution $x^{(t+1)}$ for, say cuckoo i, a Lévy flight is performed

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus L\acute{e}vy(\beta) \tag{1}$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem of interests. In most cases, we can use $\alpha = 1$.

The product $\oplus$ means entry-wise walk while multiplications. Lévy flights essentially provide a random walk while their random steps are drawn from a Lévy Distribution for large steps

$$L\acute{e}vy \sim u = t^{-1-\beta}(0 < \beta \leq 2) \tag{2}$$

this has an infinite variance with an infinite mean. Here the consecutive jumps/steps of a cuckoo essentially form a random walk process which obeys a power-law step-length distribution with a heavy tail. In addition, a fraction p_a of the worst nests can be abandoned so that new nests can be built at new locations by random walks and mixing. The mixing of the eggs/solutions can be performed by random permutation according to the similarity/difference to the host eggs. Obviously, the generation of step sizes samples is not trivial using Lévy flights. A simple scheme discussed in detail by Yang can be summarized as

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus L\acute{e}vy(\beta) \sim 0.01 \frac{u}{|v|}(x_i^{(t)} - x_b^{(t)}) \tag{3}$$

Where u and v are drawn from normal distributions. That is

$$u \sim N(0, \sigma_u^2), v \sim N(0, \sigma_v^2) \tag{4}$$

With $\sigma_u = \{\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\}^{1/\beta}$, $\sigma_v = 1$. Here Γ is the standard Gamma function.

3 A Cuckoo Search Algorithm Base on Gauss Distribution (GCS)

Lévy flight essentially provide a random walk while their random steps are drawn from a Lévy distribution for large steps (2), Which has an infinite variance with an infinite mean. Here the consecutive jumps/steps of a cuckoo essentially from a random walk process which obeys a power-law step-length distribution with a heavy tail. Given enough computation, the CS will always find the optimum [5], but, as the search relies entirely on random walks, a fast convergence and precision cannot be guaranteed. Presented here for the first time, the modifications to the method are made with the aim of increasing the convergence rate and precision, but lose the attractive features of the original method. We use

$$\sigma_s = \sigma_0 exp(-\mu k) \tag{5}$$

where σ_0 and μ are constants, k is current generation. we use (5) instead of (1). when generating new solutions $x^{(t+1)}$for, say cuckoo i, a diminishing gauss distribution is performed.

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus \sigma_s \tag{6}$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem of interests. In most cases, we can use $\alpha = 1$. In order to accommodate the difference between solution qualities.

Cuckoo search base on gauss distribution algorithm:

begin

Objective function $f(x), x = (x_1, x_2, ...x_d)^T$

Generate initial population of n *host nests* $x_i (i = 1, 2, ..., n)$

While (t <Max Generation) or (stop criterion)

Get a cuckoo randomly by gauss distribution

Evaluate its quality/fitness F_i

Choose a nest among n(say,j)randomly

If($F_i > F_j$*)*

replace j by the new soluton;

End

A fraction(P_a*) of worse nests are abandoned and new ones are built;*

keep the best solutions(or nests with quality solutions);

Rank the solutions and find the current best

End while

Postprocess results and visualization

End

4 Implementation and Numerical Experiments

4.1 Testing function

In this section, we test on six different functions to verify the algorithm proposed in this paper is feasible and effective such as Table 1. The algorithm is coded in Matlab 7.1, and run on CPU T3100, 1.90GHZ with 2GB memory capacity. The parameters are set as follows: itermax=200, p_a=0.25, μ=0.0001, σ_0=$\frac{1}{2}$.

To avoid the influence of random, every function in each algorithm is run respectively 20 trials. Statistical results such as table 2.

Table 1: Testing function

Function	Dimensions	Domain	Theoretical
Rosenbrock	10	[-100,100]	0
Sphere	50	[-5.12,5.12]	0
Rastrigin	20	[-5.12,5.12]	0
Ackley	10	[-32.768,32.768]	0
Easom	2	[100,100]	-1
Griewank	100	[-600,600]	0

Table 2: Experimental results under different functions

Function	Algorithm	Minimum fitness	Maximum fitness	Average fitness	Variance
Rosenbrock	CS	462.9039	3.1197e+003	1.4446e+003	6.7116e+005
	GCS	4.8562	158.8805	25.4291	1.4115e+003
Sphere	CS	7.4618	18.0782	11.7679	8.1463
	GCS	0.8318	3.0577	1.8499	0.3465
Rastrigin	CS	111.8739	131.4907	120.5582	32.4853
	GCS	106.2796	130.0725	114.5563	42.6203
Ackley	CS	2.4898	5.1542	3.3210	0.5428
	GCS	1.5285e-005	1.1551	0.0580	0.0667
Easom	CS	-1.0000	-0.9952	-0.9996	1.1418e-006
	GCS	-1	-1	-1	0
Griewank	CS	121.0992	199.6183	150.3869	511.1894
	GCS	82.7011	147.4886	112.0233	224.0648

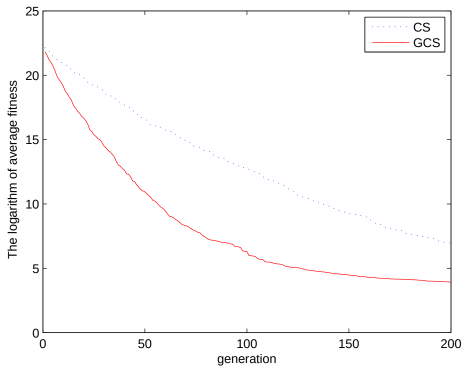

Fig. 1: Rosenbrock evolutionary curve

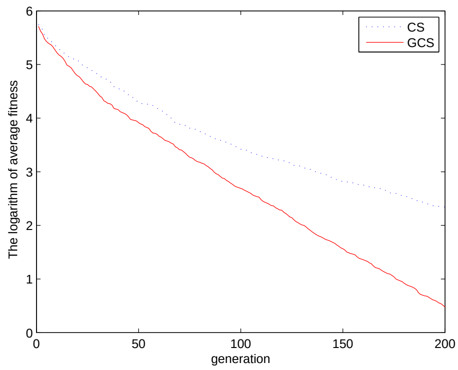

Fig. 2: Sphere evolutionary curve

Fig1∼ Fig6 are the evolutionary curve of average fitness in 20 trials. Besides Fig5, y-coordinate is the logarithm of average fitness in other figure.

Based on the above table 2, test functions have both low dimension and high dimension; both

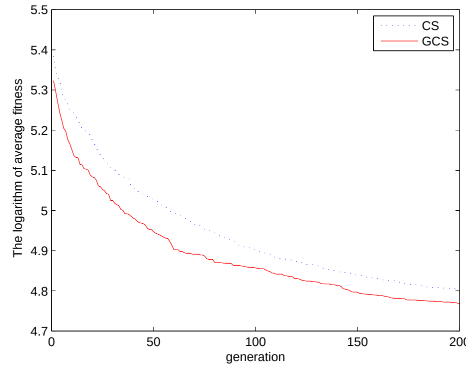

Fig. 3: Rastrigin evolutionary curve

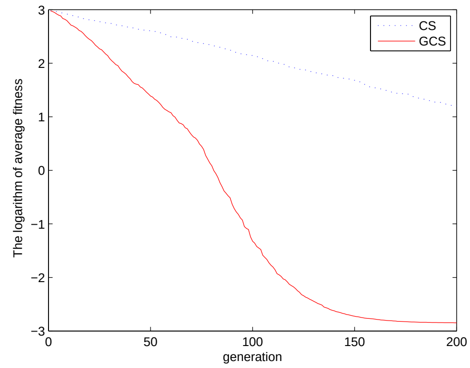

Fig. 4: Ackley evolutionary curve

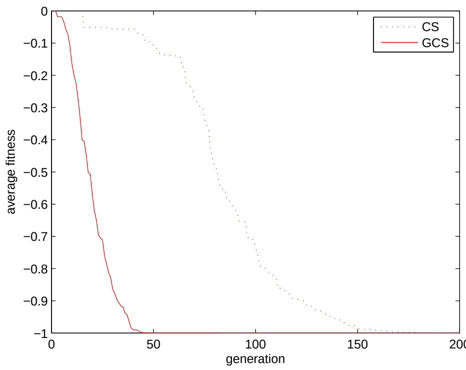

Fig. 5: Easom evolutionary curve

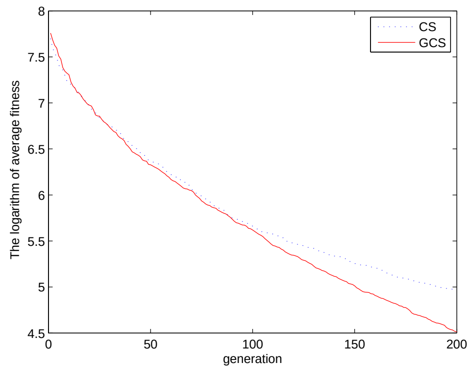

Fig. 6: Griewank evolutionary curve

single-modal function and multi-modal function. The precision of Rosenbrock function which has 10 dimensions and is improved 1419; the precision of Sphere function, it has 50 dimensions, is improved 10; the functions of Rastrigin and Griewank have respectively 20 and 100 dimensions, their precisions are improved a little; the precision of Ackley function is improved 10^5. especially Easom function, GCS reached the theoretical value. Besides, we can see that the convergence of rate GCS is faster to CS from Fig1 to Fig6.

4.2 Engineering problem

The paper quotes from the engineering problems of reference [9] as an example. To further validate the reliability and effectiveness of the modified cuckoo search algorithm. Optimization mathematical model to be described as follows:

$$minT(\alpha,\beta,\varepsilon,p_0)=\frac{2k(K\varepsilon)^{1/2}}{[(\frac{p_0+p\cos\alpha}{\sin\beta}+\frac{p\sin\alpha}{2\cos\beta})\frac{1}{z}]^{1/2}\sin\beta}[2p_0z+(\frac{\cos\alpha}{\sin\beta}+\frac{\sin\alpha}{\cos\beta})]$$

$$s.t.\begin{cases}30^o\le\alpha\le 90^o\\30^o\le\beta\le 60^o\\0.3\le\varepsilon\le 1\\40\le p_0\le 80\end{cases}$$

The formulas: α is the angle of p and horizontal axis; β is half angle of V slot; ε is a parameter of surface hardness; p_0 is the initial load; K is a parameter of rolling friction; K is allowable stress; p is all the load on moving parts; z is the number of ball.

The parameters in references [9]: $p = 50N$, $k = 0.01mm$, $K = 0.5N/mm^2$, $z = 4$. The result of CS and GCS running is as follow:

Table 3: The results of CS and GCS comparison

Algorithm	$T(N)$	α	β	ε	p_0	Average generation(20 trails)
CS	0.6825	30^o	60^o	0.3	40	20.1500
GCS	0.6825	30^o	60^o	0.3	40	13.9500

We can find that the GCS performs as well as, or better than the CS, from the above table 3. But GCS is of a higher convergence of rate, the average generation is reduced from 20.1500 to 13.9500. The feasibility and effectiveness of our approach was verified through testing by function and practical problem. The experimental results show that the GCS is significant superior to original CS.

5 Conclusions

In this paper, a novel cuckoo search optimization algorithm based on Gauss distribution (GCS) is presented. We then apply the GCS algorithm to solve standard test functions and engineering design optimization problems, the optimal solutions obtained by GCS are far better than the best solutions obtained by CS, and the GCS has a high convergence rate. Further studies can focus on hybridization with other popular algorithms and others engineering application.

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