Gaussian Bare-bones Cuckoo Search Algorithm

Hu Peng
Jiujiang University
Jiujiang, China
hu_peng@whu.edu.cn

Changshou Deng
Jiujiang University
Jiujiang, China
dengtju@aliyun.com

Hui Wang
Nanchang Institute of Technology
Nanchang, China
huiwang@whu.edu.cn

Wenjun Wang
Nanchang Institute of Technology
Nanchang, China
wangwenjun881@126.com

Xinyu Zhou
Jiangxi Normal University
Nanchang, China
xyzhou@whu.edu.cn

Zhijian Wu
Wuhan University
Wuhan, China
zhijianwu@whu.edu.cn

ABSTRACT

Cuckoo search (CS), as a relatively recent emerged swarm intelligence algorithm, is powerful and popular for the complex real parameter global optimization. However, the premature convergence has greatly affected the performance of original CS. Inspired from the individuals in the population will converge to the weighted average of global best and personal best in particle swarm optimization (PSO), we proposed a novel Gaussian bare-bones CS algorithm, named GBCS, in which the new solution for a cuckoo is generated by the Lévy flight or the Gaussian bare-bones method in a random manner. Experimental results have proved that the proposed algorithm is promising.

CCS CONCEPTS

• **Computing methodologies → Machine learning**; *Neural networks*; Bio-inspired approaches;

KEYWORDS

Evolutionary computation, Cuckoo search, Gaussian bare-bones ,Global optimization

ACM Reference Format:

Hu Peng, Changshou Deng, Hui Wang, Wenjun Wang, Xinyu Zhou, and Zhijian Wu. 2018. Gaussian Bare-bones Cuckoo Search Algorithm. In *Proceedings of the Genetic and Evolutionary Computation Conference 2018 (GECCO '18)*, Jennifer B. Sartor, Theo D'Hondt, and Wolfgang De Meuter (Eds.). ACM, New York, NY, USA, Article 4, 2 pages. https://doi.org/10.1145/3205651.3205666

1 INTRODUCTION

Cuckoo search (CS) algorithm proposed by Yang [6] is a new swarm intelligence algorithm, which simulates by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds. Since its simple concept, easy implementation and effectiveness for the complex real parameter global optimization, CS algorithm has attracted much attention in optimization community [3–5].

GECCO '18, July 15–19, 2018, Kyoto, Japan

ACM ISBN 978-1-4503-5764-7/18/07…$15.00
https://doi.org/10.1145/3205651.3205666

In CS, the new solution creation strategy plays a key role, in which the new solution for a cuckoo is generated by the Lévy flight. However, the search process is slow, because the Lévy flight is a random walk which obeys a power-length distribution with a heavy tail and the new solutions should be far from the best. Based on these observations and inspiring from the concept of the individuals in the population will converge to the weighted average of global best (*gbest*) and personal best (*pbest*), we design a Gaussian bare-bones CS algorithm, named GBCS, in which the new solution for a cuckoo is generated by the Lévy flight or the Gaussian bare-bones method in a random manner. The experiments are conducted on a set of widely used benchmark functions. Experimental results have proved that the proposed algorithm is promising.

The rest of this paper is structured as follows. In Section 2 presents the details of the our proposed GBFA algorithm. Experimental studies are described in Section 3. Section 4 concludes the work.

2 GAUSSIAN BARE-BONES CUCKOO SEARCH ALGORITHM (GBCS)

Particle swarm optimization (PSO)[2] is one of the most popular swarm intelligence algorithm inspired from the hunting behavior of birds and fish groups. In PSO, each individual is called a particle, which represents a potential solution. Each particle is attracted by its personal best position (*pbest*) and the global best position (*gbest*) to search for the optimal solution. The convergence of PSO is analyzed in [1], and it is proved that the particles in the population will converge to the weighted average of *gbest* and *pbest*. Based on these consideration, we design a Gaussian bare-bones CS algorithm, named GBCS, in which the new solution for a cuckoo is generated by the Lévy flight or the Gaussian bare-bones method in a random manner.

The new solution creation strategy based on Gaussian bare-bones is formulated as follow:

$$x_{i,d} = N(\mu,\sigma) \tag{1}$$

$$\mu = \left(x_{best,d} + x_{i,d}\right)/2,\ \sigma = \left|x_{best,d} - x_{i,d}\right| \tag{2}$$

where X_{best} is the best solution in the current population, X_i is the ith solution, and $N(.)$ represents a Gaussian distribution with mean μ and variance σ.

In the original CS, a new solution X_i for the ith cuckoo is generated by the following Lévy flight:

$$X_i = X_i + \alpha \oplus L\acute{e}vy \tag{3}$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem of interest. In GBCS, the α is dynamic and generated by $N(0.2, 0.05)$

Then, in GBCS, the new solution is updated as follows:

$$X_i = \begin{cases} GB\ method, & if\ rand < 0.5 \\ L\acute{e}vy\ flight, & otherwise \end{cases} \tag{4}$$

This new solution creation strategy combined the Lévy flight and the Gaussian bare-bones method, which can effectively balance the exploration and exploitation of new algorithm. The details of GBCS algorithm describes in the Algorithm 1.

Algorithm 1 The Proposed GBCS algorithm

```
1:  Randomly initialize population P with N host nest
2:  Evaluate the fitness value of each initial solution
3:  while t < MaxGen do
4:      Get a Cuckoo (say i) via Lévy flight or Gaussian bare-bones
        method according to the Eq.4
5:      Evaluate fitness for the cuckoo i
6:      Choose a nest among N (say j) randomly
7:      if f_i is better than f_j then
8:          Replace j by the new solution
9:      end if
10:     A fraction (pa) of worse nests are abandoned and new ones
        are built
11:     Update the global best solution
12:     t = t + 1;
13: end while
```

3 EXPERIMENTAL STUDY

There are thirteen benchmark functions are used in the following experimental studies and the detailed descriptions of these functions can be found in [7]. All these problems should be minimized and the D is set to 30. These functions are widely used in the evolutionary computation community, among the thirteen functions, $f_1 \sim f_7$ are unimodal functions, $f_8 \sim f_{13}$ are multimodal functions with many local minima.

To evaluate the quality of the proposed GBCS algorithm, we have conducted a comparison among the original CS and GBCS. For a fair comparison, the same parameter settings were employed for the two contestant algorithms, that is, $N = D$, $pa = 0.25$, and $MaxFEs = 3.0E + 05$. All the experiments are done on a computer with 2.8GHz Dual-core Processor and 4GB RAM under Windows 7 platform and all algorithms are implemented in Matlab 2014. Each algorithm independently runs 30 times for each test function, and the mean and standard deviation of the function error values among 30 runs are recorded. In order to have statistically sound conclusions, Wilcoxon's rank sum test at a 0.05 significance level is introduced to analyse the experiment result.

The mean errors and the standard deviations of the two comparison algorithms on each test function are summarized in Table 1. In Table 1 , it is obvious that GBCS is significantly better than CS on 10 out of 13 test functions.

Table 1: Experimental results of original CS and GBCS for all test functions at D=30 and comparison results based on Wilcoxon's rank sum test

F	CS Mean Error±Std Dev	GBCS Mean Error±Std Dev
f_1	1.22E−30±1.35E−30−	1.00E−80±2.69E−80
f_2	2.88E−14±2.11E−14−	8.65E−50±1.47E−49
f_3	1.43E−03±1.23E−03−	2.28E−03±1.34E−03
f_4	1.55E+00±1.27E+00−	4.84E−08±5.69E−08
f_5	8.32E+00±2.52E+00−	5.58E−02±1.26E−01
f_6	0.00E+00±0.00E+00≈	0.00E+00±0.00E+00
f_7	1.22E−02±4.04E−03−	3.96E−03±1.05E−03
f_8	1.88E+03±3.69E+02≈	1.67E+03±5.71E+02
f_9	2.73E+01±4.41E+00−	1.48E+01±5.26E+00
f_{10}	1.32E−01±3.37E−01−	3.55E−15±0.00E+00
f_{11}	1.85E−17±9.96E−17≈	4.92E−04±2.65E−03
f_{12}	1.31E−14±7.06E−14−	1.58E−32±1.49E−34
f_{13}	6.88E−28±1.57E−27−	1.47E−32±3.74E−33
−/+/≈	10/0/3	−−

4 CONCLUSION

In this paper, a novel Gaussian bare-bones CS algorithm, named GBCS, is presented, in which the new solution for a cuckoo is generated by the Lévy flight or the Gaussian bare-bones method in a random manner. The new solution creation strategy enables the GBCS can get the faster convergence since the the best information have utilized effectively. The performance of GBCS is investigated by comparing with original CS and the results show that GBCS achieves better convergence performance. In the future, how to generalize our work to solve some real-world application problems remains an attractive topic.

ACKNOWLEDGEMENTS

This work is supported by the National Natural Science Foundation of China (No.61763019, No.61603163, and No.61663028).

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