A Hybrid CS/PSO Algorithm for Global Optimization

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Abstract. This paper presents the hybrid approach of two nature inspired metaheuristic algorithms; Cuckoo Search (CS) and Particle Swarm Optimization (PSO) for solving optimization problems. Cuckoo birds lay their own eggs to other host birds. If the host birds discover the alien birds, they will leave the nest or throw the egg away. Cuckoo birds migrate to the environments that reduce the chance of their eggs to be discovered by the host birds. In standard CS, cuckoo birds experience new places by the Lévy Flight. In the proposed hybrid algorithm, cuckoo birds are aware of each other positions and make use of swarm intelligence in PSO in order to reach to better solutions. Experimental results are examined with some standard benchmark functions and the results show a promising performance of this algorithm.

Keywords: Cuckoo Search, Global optimization, PSO, Metaheuristic and Hybrid evolutionary algorithm.

1 Introduction

Finding optimal solutions for many problems is very difficult to deal with. The complexity of such problems makes it impossible to look for every possible solution or combination [1]. However, because of their complexity the use of approximation algorithms in order to find approximate solutions is getting more popular in the past few years [2]. Among these algorithms, modern metaheuristics are becoming popular, which leads to a new branch of optimization, named metaheuristic optimization. Most of these algorithms are nature inspired [3], some of which have been proposed for optimization problems, for example, Genetic Algorithm (GA) [4], Harmony Search (HS) [5], Ant Colony Optimization (ACO) [6], Imperialist Competitive Algorithm (ICA) [7] and Artificial Bee Colony [8].

Yang and Deb formulated a new metaheuristic algorithm, called Cuckoo Search in 2009 [9]. This algorithm is inspired by life of cuckoo bird in combination with Lévy Flight behavior of some birds and fruit flies. The studies show the CS algorithm is very promising and could outperform some known algorithms, such as PSO and GA.

PSO was formulated by Kennedy and Eberhart in 1995 [10]. It is an evolutionary computation technique which is inspired by social behavior of swarms. This algorithm is the simulation of the social behavior of birds, like the choreography of a bird flock. Each individual in the population is a particle and gets a random value in

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the initialization. Each particle despite the position vector contains the best personal experience and a velocity vector. The particle's velocity and its best personal experience and the global best position all together determines a particle next movement. PSO has variety of usages such as [11] and [12].

CS and PSO are metaheuristic algorithms and are inspired by birds. In this paper cuckoo birds communicate in order to inform each other from the suitable place for laying egg. This is achieved by adding the swarm intelligence which is used in PSO.

Some related works is presented in section 2. Standard CS is discussed in section 3. Section 4 provides an overview of PSO. Section 5 gives a hybrid approach of CS with PSO and Section 6 presents the detailed experimental results to compare the performance of the proposed algorithm with other algorithms.

2 Related Works

Layeb introduced a new hybridization between quantum inspired and cuckoo search for knapsack problem [13]. This hybrid algorithm achieves better balance between exploration and exploitation and experimental results shows convincing results.

A modified CS was proposed by Tuba, Subotic and Stanarevic in 2011 by biasing the step size in the original algorithm [14]. This is achieved by determining the step size from the sorted rather than only permuted fitness matrix.

Another modification of the standard Cuckoo Search was made by Walton, Hassan, Morgan and Brown with the aim to speed up convergence [15]. The modification involves the additional step of information exchange between the top eggs. It was shown that Modified Cuckoo Search (MCS) outperforms the standard cuckoo search and other algorithms, in terms of convergence rates, when applied to a series of standard optimization benchmark objective functions.

Valian, Mohanna and Tavakoli applied cuckoo search to train neural networks with improved performance [16] and was employed for benchmark classification problems and the results shows the effectiveness of the introduce algorithm.

3 Cuckoo Search

This algorithm is inspired by the special lifestyle of a bird called 'cuckoo'. Cuckoo birds never build their own nests and instead lay their eggs in the nest of other host birds. If host birds discover the eggs are not their own, they will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. On the other hand cuckoo birds carefully mimic the color and pattern of the eggs of host birds. In general, the cuckoo eggs hatch slightly earlier than their host eggs. Once the first cuckoo chick is hatched, the first instinct action it will take is to evict the host eggs by blindly propelling the eggs out of the nest, which increases the cuckoo chick's share of food provided by its host bird. Studies also show that a cuckoo chick can also mimic the call of host chicks to gain access to more feeding opportunity [9].

In nature, animals' path for searching food is in a random way which effectively is a random walk because the next move is based on the current location and the transition probability to the next location. Various studies have shown that fruit flies or Drosophila melanogaster; explore their landscape using a series of straight flight path punctuated by a sudden 90° turn, leading to a Lévy-flight-style pattern. Such behavior has been applied to optimization and optimal search, and preliminary results show its promising capability [9], [17]. Figure 1 shows an example of the Lévy flights path [18].

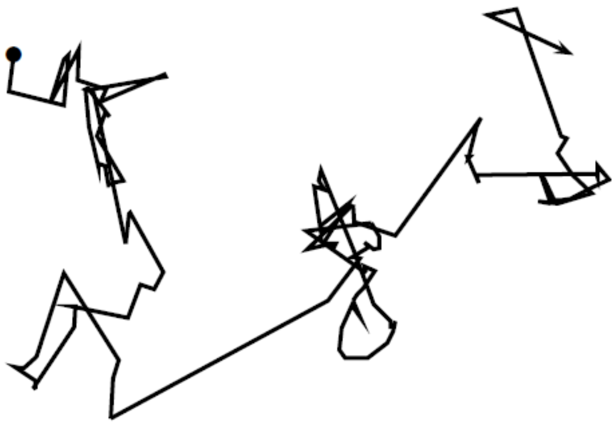


Fig. 1. Example of Lévy flights path [18]

Cuckoo search is introduced in three idealized rules: 1) Each cuckoo lays one egg at a time and dumps it in a randomly chosen nest. 2) The best nest with high quality of eggs (solutions) will carry over to the next generation. 3) The number of available host nests is fixed, and a host can discover an alien egg with a probability $P_a \in [0,1]$.

For maximization problem the fitness of a solution can be proportional to the value of its objective function. Other forms of fitness can be defined in a similar way to the fitness function in other evolutionary algorithm. A simple representation where one egg in a nest represents a solution and a cuckoo egg represents a new solution is used here. The aim is to use the new and potentially better solutions (cuckoos) to replace worse solutions that are in the nests. When generating new solutions $x^{(t+1)}$ for, say cuckoo i, a Lévy flight is performed using the following equation:

$$x_i^{(t+1)} = x_i^t + \alpha \oplus \text{Lévy}(\lambda) \,. \tag{1}$$

Where $\alpha > 0$ is the step size which should be related to the scales of the problem of interest. The product $\oplus$ means entry-wise multiplication. The above equation is essentially the stochastic equation for random walk. In general, a random walk is a Markov chain whose next status/location only depends on the current location (the first term in the above equation) and the transition probability (the second term).

The Lévy flight essentially provides a random walk while the random step length is drawn from a Lévy distribution which has an infinite variance with an infinite mean.

$$Lévy \sim u = t^{-\lambda}, \qquad -1 < \lambda < 3 . \tag{2}$$

Studies show that Lévy flights can maximize the efficiency of resource searches in uncertain environments [18]. 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.

4 Particle Swarm Optimization

Swarm Intelligence (SI) is an innovative distributed intelligent paradigm for solving optimization problems that originally took its inspiration from the biological examples by swarming, flocking and herding phenomena in vertebrates [19].

PSO is an evolutionary algorithm which is inspired by the feeding birds or fish and proposed by Kennedy and Eberhart in 1955. This algorithm like other evolutionary algorithms starts with random initial solutions and begins the process of finding the global optimum. In this algorithm, we call each solution a *particle*. Each particle moves around in the search space with a velocity. The best position explored for a particle so far is recorded and is called *pbest*. Moreover, each particle knows the best *pbest* among all the particles which is called *gbest*. By considering *pbest, gbest* and the velocity of each particle the update rule for their position is as the following equations:

$$V_{t+1} = W_t * V_t + C_1 * rand(\quad) * (pbest - x_t) + C_2 * rand(\quad) * (gbest - x_t) . \tag{3}$$

$$x_{t+1} = x_t + V_{t+1} . \tag{4}$$

Where W is inertia weight which shows the effect of previous velocity vector (V_t) on the new vector, C_1 and C_2 are acceleration constants and $rand(\quad)$ is a random function in the range [0, 1] and x_t is current position of the particle.

5 Hybrid CS/PSO Algorithm

In this section, we explore the details of the proposed hybrid algorithm. As mentioned in section 3, the nature of cuckoo birds is that they do not raise their own eggs and never build their own nests, instead they lay their eggs in the nest of other host birds. If the alien egg is discovered by the host bird, it will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. Thus cuckoo birds always are looking for a better place in order to decrease the chance of their eggs to be discovered. In the proposed hybrid algorithm, the ability of communication for cuckoo birds has been added. The goal of this communication is to inform each other from their position and help each other to immigrate to a better place. Each cuckoo bird will record the best personal experience as *pbest* during its own life. In addition, the best *pbest* among all the birds is called *gbest*. The cuckoo birds' communication is established through the *pbest*, *gbest* and they update their position using these parameters and also the velocity of each one. The update rule for cuckoo i's position is as the following:

$$V_{t+1}{}^{i} = W_t{}^{i} * V_t{}^{i} + C_1 * rand(\ \ ) * \left(pbest - x_t^i\right) + C_2 * rand(\ \ ) * \left(gbest - x_t^i\right) . \tag{5}$$

$$x_{t+1}^i = x_t^i + V_{t+1}{}^{i} \ . \tag{6}$$

Where W is inertia weight which shows the effect of previous velocity vector ($V_t{}^{i}$) on the new vector, C_1 and C_2 are acceleration constants and $rand(\ \ )$ is a random function in the range [0, 1] and x_t^i is current position of the cuckoo. The pseudo-code of the CS/PSO is presented as bellow:

```
begin
  Objective function f(x), x = (x_1, ..., x_d)^T;
  Initial a population of n host nests x_i (i = 1,2,...,n);
  While (t<MaxGeneration) or (stop criterion);
    Get a cuckoo (say i) randomly by Lévy flights
    and record pbest;
    Evaluate its quality/fitness F_i;
    Choose a nest among n (say j) randomly;
    if (F_i > F_j),
      Replace j by the new solution;
    end
    Move cuckoo birds using equation 5 and 6;
    Abandon a fraction (P_a) of worse nests
      [and build new ones at new locations via Lévy
      flights];
    Keep the best solutions (or nests with quality
    solutions);
    Rank the solutions and find the current best;
  end while
  Post process results and visualization;
end
```

6 Evaluation and Experimental Results

In this section, we show experimental results which evaluate our hybrid CS/PSO proposed algorithm. In the field of evolutionary computation, it is common to compare different algorithms using benchmark functions, especially when the test involves function optimization [20]. Thus, we applied the proposed algorithm for some classical benchmark functions which is shown in table 1. Initial range, formulation, characteristics and the dimensions of these problems are listed in table 1. If a function has more than one local optimum, this function is called multimodal. Multimodal functions are used to test the ability of algorithms escaping from local minima. A p-variable separable function can be expressed as the sum of p functions of one variable. Non-separable functions have interrelation among their variables. Therefore, non-separable functions are more difficult than the separable functions [20]. In table 1, characteristics of each function are given in the third column. In this column, M means that the function is multimodal, while U means that the function is unimodal. If the function is separable, abbreviation S is used to indicate this specification. Letter N refers that the function is non-separable.

Table 1. The Benchmark functions

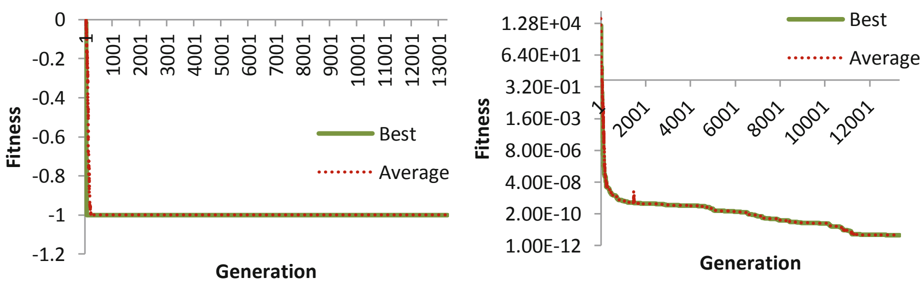
Function	Formulation	Type	DIM	Range
F1 (Ackley)	$-20e^{-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2}} - e^{\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)} + 20 + e$	MN	30	[-32,32]
F2 (Dixon-Price)	$(x_1-1)^2 + \sum_{i=2}^{n} i(2x_i^2 - x_{i-1})^2$	UN	30	[-10,10]
F3 (Easom)	$-\cos(x_1)\cos(x_2)\exp(-(x_1-\pi)^2 - (x_2-\pi)^2)$	UN	2	[-100,100]
F4 (Griewank)	$1 + \sum_{i=1}^{D}\left(\frac{x_i^2}{4000}\right) - \prod_{i=1}^{2}\left(\cos(\frac{x_i}{\sqrt{i}})\right)$	MN	30	[-600,600]
F5 (Powell)	$\sum_{i=1}^{n/k}(x_{4i-3}+10x_{4i-2})^2 + 5\,(x_{4i-1}-x_{4i})^2 + (x_{4i-2}-x_{4i-1})^4 + 10(x_{4i-3}-x_{4i})^4$	UN	24	[-4,5]
F6 (Rastrigin)	$\sum_{i=1}^{D}(x_i^2 - 10\cos(2\pi x_i) + 10)$	MS	30	[-5.12,5.12]
F7 (Schwefel)	$\sum_{i=1}^{n} -x_i\sin(\sqrt{\lvert x_i\rvert})$	MS	30	[-500,500]
F8 (Schwefel 1.2)	$\sum_{i=1}^{D}\left(\sum_{j=1}^{i} x_j\right)^2$	UN	30	[-100,100]
F9 (SumSquares)	$\sum_{i=1}^{D} i^2 x_i^2$	US	30	[-10,10]

The simulation results are compared with results of Cuckoo Search [21], a modernized implementation of PSO, which is known as PSO-2007 [22], Differential Evolution (DE) [23] and Artificial Bee Colony (ABC) algorithm [8]. We used 9 benchmark functions in [21] in order to test the performance of the CK, PSO, DE,

Table 2. Experimental results with CS/PSO

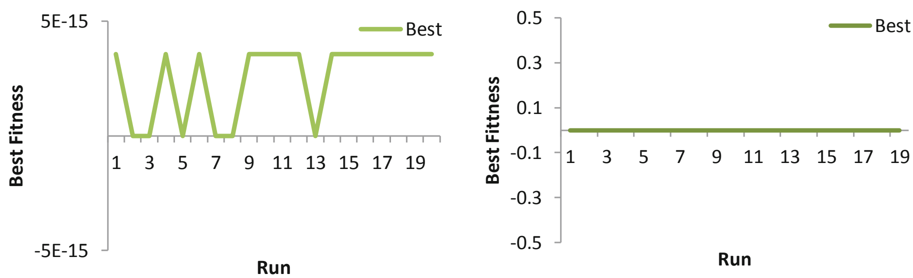
		CK	**PSO**	**DE**	**ABC**	**CS/PSO**
F1	Min	4.40E-15	8.00E-15	4.40E-15	2.22E-14	0.00E+00
	Mean	4.40E-15	8.00E-15	4.40E-15	3.00E-14	3.55E-15
	StdDev	0.00E+00	0.00E+00	0.00E+00	2.50E-15	1.67E-15
F2	Min	6.67E-01	6.67E-01	6.67E-01	1.40E-15	6.67E-01
	Mean	6.67E-01	3.27E+01	6.67E-01	2.30E-15	6.67E-01
	StdDev	5.00E-16	9.86E+01	2.00E-16	5.00E-16	2.42E-16
F3	Min	-1.00E+00	-1.00E+00	-1.00E+00	-1.00E+00	-1.00E+00
	Mean	-3.00E-01	-1.00E+00	-1.00E+00	-1.00E+00	-1.00E+00
	StdDev	4.70E-01	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F4	Min	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Mean	0.00E+00	9.23E-03	1.11E-03	0.00E+00	0.00E+00
	StdDev	0.00E+00	1.06E-02	3.44E-03	0.00E+00	0.00E+00
F5	Min	7.98E-08	2.11E-05	0.00E+00	2.72E-04	4.80E-13
	Mean	1.51E-07	5.18E-05	0.00E+00	4.49E-04	3.39E-11
	StdDev	5.45E-08	2.16E-05	0.00E+00	6.66E-05	5.17E-11
F6	Min	3.81E-04	1.39E+01	7.96E+00	0.00E+00	0.00E+00
	Mean	1.28E+00	2.80E+01	1.54E+01	0.00E+00	0.00E+00
	StdDev	1.04E+00	7.87E+00	4.96E+00	0.00E+00	0.00E+00
F7	Min	-1.26E+04	-1.04E+04	-1.22E+04	-1.26E+04	-8.84E+03
	Mean	-1.25E+04	-8.93E+03	-1.19E+04	-1.26E+04	-7.33E+03
	StdDev	7.64E+01	9.12E+02	2.04E+02	1.87E-12	7.73E+02
F8	Min	0.00E+00	1.28E-13	0.00E+00	1.08E+01	0.00E+00
	Mean	0.00E+00	7.39E-10	0.00E+00	4.75E+01	0.00E+00
	StdDev	0.00E+00	2.43E-09	0.00E+00	2.32E+01	0.00E+00
F9	Min	0.00E+00	0.00E+00	0.00E+00	3.00E-16	0.00E+00
	Mean	0.00E+00	0.00E+00	0.00E+00	4.00E-16	0.00E+00
	StdDev	0.00E+00	0.00E+00	0.00E+00	1.00E-16	0.00E+00

ABC and CS/PSO algorithms. The best values, the mean best values and standard deviation are given in table 2. Convergence diagram for functions F3 and F5 are presented in Figure 2. Figure 3 shows the stability diagrams for F1 and F8. In order to make comparison coherently, the global minimum values below 10^{-16} are assumed to be 0 in all experiments. 20 runs of algorithm were needed for each function and the maximum evaluation number was 2,000,000 for all functions. The parameter settings of CS/PSO are described as follows: The population size is set to 50 and the probability of discovery, P_a is set to 0.25. Acceleration constants $C1$, $C2$ are set to 1.5 and the inertia weight is 0.7. Settings of the algorithms CK, PSO, DE and ABC can be found in [21].



(a) (b)

Fig. 2. Convergence diagram for functions: (a) *F3* and (b) *F5*



(a) (b)

Fig. 3. Stability diagram for functions: (a) *F1* and (b) *F8*

7 Conclusion and Future Works

In this paper we combined two nature inspired algorithms and introduced the CS/PSO algorithm. With a profound look into the cuckoo birds' life style, we can observe the standard CS algorithm can be extended. In proposed algorithm we added swarm intelligence to the cuckoo birds, in order to increase the chance of their eggs survival. By the use of swarm intelligence it can be seen the hybrid algorithm observe more search space and can effectively reach to better solutions.

CS/PSO was evaluated on some benchmark functions and the result show that the proposed hybrid algorithm outperforms the CK with 80%, PSO-2007 with 85%, DE with 60% and ABC with more than 65% of the total time in comparison.

Our future research would include the hybridization of the CS algorithm with other nature inspired algorithms. Also the future works can include the parallelization of the cuckoo search algorithm to provide considerable gains in term of performance.

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