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Mini Review

Cuckoo Search and Firefly Algorithms-Biologically Inspired Algorithms

SM Kamalapur*

KK Wagh Institute of Engineering Education & Research, India

***Corresponding author:** SM Kamalapur, PhD, KK Wagh Institute of Engineering Education & Research, India, Email: smkamalapur@kkwagh.edu.in

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Abstract

Optimization is an important subject with a wide range of applications. Biologically inspired algorithms are becoming powerful to solve optimization problem. This paper intends to provide brief overview of two biologically inspired algorithms namely cuckoo search and firefly algorithms. Application areas of these algorithms are listed in the paper.

Introduction

Optimization is a process of finding an optimal solution for a problem. An optimization problem is finding values of the variables that minimize or maximize the objective function while satisfying the constraints. Optimization is important subject with a wide range of applications. There are many optimization algorithms in the literature and no single algorithm is suitable for all problems [1]. Algorithms can be either deterministic or stochastic. Deterministic algorithm works in a mechanically deterministic manner without any random nature. On the other hand, stochastic algorithm has some randomness in the algorithm. With same initial point it may reach to a different point for every run of the algorithm. Metaheuristics are becoming increasingly popular. Metheuristics algorithms are stochastic algorithms.

A metaheuristic is formally defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions. [2]. Metaheuristics are strategies that "guide" the search process and are not problem-specific [3]. But it may make use of domain-specific knowledge as heuristics strategy.

Metaheuristic algorithms are often nature-inspired, and they are now among the most widely used algorithms for optimization. Metaheuristic algorithms include genetic algorithms, simulated annealing, ant and bee algorithms, bat algorithm, particle swarm optimization, harmony search, firefly algorithm, cuckoo search and others [4-10]. Biologically or nature inspired algorithms are becoming powerful in modern numerical optimization [11-15].

Cuckoo Search Algorithm

Yang & Deb [7] proposed a method of global optimization based on the behavior of cuckoos. In addition, this algorithm is enhanced by the so-called Lvy flights [16,17], rather than by simple isotropic random walks.

Some cuckoo species obligate brood parasitism. They lay their eggs in the nests of host birds. Parasitic cuckoos often choose a nest where the host bird just laid its own eggs. Generally the cuckoo eggs are hatched slightly earlier than their host eggs. Once the first cuckoo chick is hatched, its first instinct action is to evict the host eggs. Host eggs are blindly propelled out of the nest. Host bird may discover that the eggs are not their own. In this case host bird will either throw the cuckoo eggs away or simply abandon the nests and build new ones. Some female parasitic cuckoos can imitate the colors and patterns of the eggs of chosen host bird. This is to reduce the probability of the eggs being abandoned. A cuckoo chick can also imitate the call of host chicks. This is to gain access to more feeding opportunity.

Cuckoo search follow three idealized rules

i. Each cuckoo lays one egg at a time, and dumps it in a randomly chosen nest.

ii. The best nests with high-quality eggs will be carried over to the next generations.

iii. The number of available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability. In this case, the host bird can either get rid of the egg, or simply abandon the nest and build a completely new nest.

```
begin
Objective function f(x), x = (x1,...., xd)^T
Generate initial population of k host nests xi (i = 1, 2, ..., k)
while (t <MaxGeneration) or (stop criterion)
    Get a cuckoo randomly by L´evy flights
    evaluate its quality/fitness Fi,
    Choose a nest among k (say, j) randomly
    if (Fi > Fj ),
        replace j by the new solution;
    end
    A fraction (pa) 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
```

Figure 1: Cuckoo Search (CS) is summarized as the pseudo code.

The basic the Cuckoo Search (CS) is summarized as the pseudo code shown in Figure 1.

New solutions x(t+1) are generated using L´evy flight.

e.g A L´evy flight is performed for cuckoo i, is

$x_i(t+1)=x_i(t+1)+\alpha \oplus L'evy(\lambda)$ (1)

In most cases, α=1. The product ⊕ means entrywise multiplications.

Application of the CS algorithm

a. Engineering optimization problems

b. NP hard combinatorial optimization problems

c. Data fusion in wireless sensor networks

d. Nanoelectronic technology based operation-amplifier

e. (OP-AMP)

f. Train neural network

g. Manufacturing scheduling

h.Nurse scheduling problem

Firefly Algorithm (FA)

The flashing light of fireflies is an astonishing sight. There are about two thousand firefly species. Most of these fireflies produce short and rhythmic flashes. The flashing light is produced by a process of bioluminescence. These flashes are used to attract mating partners (communication), to attract potential prey or as a protective warning mechanism.

Firefly algorithm follows three idealized rules-

A. All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex

B. Attractiveness is proportional to the brightness, and they both decrease as their distance increases.

C. The brightness of a firefly determined by the objective function.

The basic the firefly algorithm is summarized as the pseudo code shown in Figure 2.

Advantages of FA

a. FA can deal with highly non- linear, multi-modal optimization problems naturally and efficiently.

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```
Objective function f(x), f(x), x = (x1,...., xd)^T
Generate initial population of fireflies xi (i = 1, 2,...., k)Light intensity Ii
at xi is determined by f(xi)
Define light absorption coefficient
While (t <MaxGeneration)
        for i = 1 : n all n fireflies
                for j = 1 : i all n fireflies
                                if begin
                        (Ij > Ii)
                                Move firefly i towards j in d-dimension;
                        end if
                        Attractiveness varies with distance r via exp[−r]
                        Evaluate new solutions and update light intensity
                end for j
        end for i
        Rank the fireflies and find the current best
end while
Postprocess results and visualization
```

Figure 2: Firefly algorithm is summarized as the pseudo code.

b. The speed of convergence of FA is very high in probability of finding the global optimized answer.

c. It has the flexibility of integration with other optimization techniques to form hybrid tools.

d. It does not require a good initial solution to start its iteration process.

Application of the FA algorithm

Travelling salesman problem

Digital image compression and image processing

Feature Selection and fault detection

Antenna design

Structural design

Scheduling

Chemical phase equilibrium

Conclusion

Biologically or nature inspired algorithms are becoming powerful in modern numerical optimization. Two biologically inspired algorithms namely cuckoo search and firefly algorithm are discussed here. These algorithms can be applied to many real world applications.

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