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 an 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 algorithms work in a mechanically deterministic manner without any random nature. On the other hand, stochastic algorithms have some randomness in the algorithm. With the same initial point, they may reach a different point for every run of the algorithm. Metaheuristics are becoming increasingly popular. Metaheuristic algorithms are stochastic algorithms.

Metaheuristics are formalized as iterative generation processes which guide 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 they 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 and Deb [7] proposed a method of global optimization based on the behavior of cuckoos. In addition, this algorithm is enhanced by the so-called Lévy 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 birds may discover that the eggs are not their own. In this case, the 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 birds. 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 follows 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.
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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.

\[ x_i(t+1) = x_i(t+1) + \alpha \circ \text{Levy}(\lambda) \]

In most cases, $\alpha=1$. The product $\circ$ means entrywise multiplications.

Application of the CS algorithm

- Engineering optimization problems
- NP hard combinatorial optimization problems
- Data fusion in wireless sensor networks
- Nano electronic technology based operation-amplifier (OP-AMP)
- Train neural network
- Manufacturing scheduling
- 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.
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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