**Cuckoo Search Optimization (CSO) Via Levy Flights for heart disease prediction**

Cuckoo search is an optimization algorithm developed by Xin-she Yang and Suash Deb. It was inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds (of other species).

**Algorithm:**

Objective function:

Generate an initial population of host nests;

While ( < MaxGeneration) or (stop criterion)

  Get a cuckoo’s nest randomly and replace its solution by performing Lévy flights;

  Evaluate its quality/fitness

  Choose a nest among randomly;

  if ( > ),

    Replace by the new solution;

  end if

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

  Keep the best solutions/nests;

  Rank the solutions/nests and find the current best;

  Pass the current best solutions to the next generation;

end while

An important advantage of this algorithm is its simplicity. In fact, compared with other population- or agent-based metaheuristic algorithms such as particle swarm optimization and harmony search, there is essentially only a single parameter in CS (apart from the population size ). Therefore, it is very easy to be implemented.

Requirements:

Numpy

matplotlib

Once the installation is finished (download or cloning), go the cso folder and follow the b

from cso import CSO

Next, a fitness function (or cost function) is required. I have included four different fitness functions for example purposes namely fitness\_1, fitness\_2, fitness\_3, and fitness\_4.

Fitness-1 (Himmelblau's Function)

Minimize: f(x) = (x2 + y - 11)2 + (x + y2 - 7)2

Optimum solution: x = 3 ; y = 2

Fitness-2 (Booth's Function)

Minimize: f(x) = (x + 2y - 7)2 + (2x + y - 5)2

Optimum solution: x = 1 ; y = 3

Fitness-3 (Beale's Function)

Minimize: f(x) = (1.5 - x - xy)2 + (2.25 - x + xy2)2 + (2.625 - x + xy3)2

Optimum solution: x = 3 ; y = 0.5

Fitness-4

Maximize: f(x) = 2xy + 2x - x2 - 2y2

Optimum solution: x = 2 ; y = 1

Fitness-5 (Bivariate Michaelwicz function)

Minimize: f(x) = -sin(x)(sin2m(x2/π)) - sin(y)(sin2m(2y2/π))

When the bound is (x,y) ∈ (0,5) x (0,5) and m=10 [1]

Optimum solution: x = 2.20319 ; y = 1.57049

>>> from fitness import fitness\_1, fitness\_2, fitness\_3, fitness\_4, fitness\_5

Now, if you want, you can provide bound values for all the particles (not mandatory) and optimize (minimize or maximize) the fitness function using CSO:

NOTE: a bool variable min=True (default value) for MINIMIZATION PROBLEM and min=False for MAXIMIZATION PROBLEM

>>> CSO(fitness=fitness\_5, bound=[(0,5),(0,5)]).execute()

You will see the following similar output (there can be other minima as well):

OPTIMUM SOLUTION

> [2.2028966, 1.5707915]

OPTIMUM FITNESS

> -1.8013034

When fitness\_4 is used, observe that min=False since it is a Maximization problem.

>>> CSO(fitness=fitness\_4, bound=[(-4,4),(-4,4)], min=False).execute()

You will see the following similar output:

OPTIMUM SOLUTION

> [2.0, 1.0]

OPTIMUM FITNESS

> 2.0

Incase you want to print the fitness value for each iteration, set verbose=True (here Tmax=50 is the maximum iteration)

>>> CSO(fitness=fitness\_2, Tmax=50, verbose=True).execute()

You will see the following similar output:

Iteration: 0 | best global fitness (cost): 4.2060194

Iteration: 1 | best global fitness (cost): 4.2060194

Iteration: 2 | best global fitness (cost): 4.2060194

Iteration: 3 | best global fitness (cost): 4.2060194

Iteration: 4 | best global fitness (cost): 4.2060194

Iteration: 5 | best global fitness (cost): 3.0228358

Iteration: 6 | best global fitness (cost): 2.0454478

Iteration: 7 | best global fitness (cost): 1.647782

Iteration: 8 | best global fitness (cost): 0.2005788

Iteration: 9 | best global fitness (cost): 0.1981048

Iteration: 10 | best global fitness (cost): 0.1981048

Iteration: 11 | best global fitness (cost): 0.1981048

Iteration: 12 | best global fitness (cost): 0.1981048

Iteration: 13 | best global fitness (cost): 0.1981048

Iteration: 14 | best global fitness (cost): 0.1981048

Iteration: 15 | best global fitness (cost): 0.1981048

Iteration: 16 | best global fitness (cost): 0.1981048

Iteration: 17 | best global fitness (cost): 0.1981048

Iteration: 18 | best global fitness (cost): 0.0547217

Iteration: 19 | best global fitness (cost): 0.0367725

Iteration: 20 | best global fitness (cost): 0.0367725

Iteration: 21 | best global fitness (cost): 0.0367725

Iteration: 22 | best global fitness (cost): 0.0367725

Iteration: 23 | best global fitness (cost): 0.0367725

Iteration: 24 | best global fitness (cost): 0.0367725

Iteration: 25 | best global fitness (cost): 0.0367725

Iteration: 26 | best global fitness (cost): 0.0367725

Iteration: 27 | best global fitness (cost): 0.0367725

Iteration: 28 | best global fitness (cost): 0.0367725

Iteration: 29 | best global fitness (cost): 0.0367725

Iteration: 30 | best global fitness (cost): 0.0367725

Iteration: 31 | best global fitness (cost): 0.0367725

Iteration: 32 | best global fitness (cost): 0.0367725

Iteration: 33 | best global fitness (cost): 0.0367725

Iteration: 34 | best global fitness (cost): 0.0367725

Iteration: 35 | best global fitness (cost): 0.0367725

Iteration: 36 | best global fitness (cost): 0.0367725

Iteration: 37 | best global fitness (cost): 0.0196146

Iteration: 38 | best global fitness (cost): 0.0087851

Iteration: 39 | best global fitness (cost): 0.0087851

Iteration: 40 | best global fitness (cost): 0.0087851

Iteration: 41 | best global fitness (cost): 0.0087851

Iteration: 42 | best global fitness (cost): 0.0087851

Iteration: 43 | best global fitness (cost): 0.0087851

Iteration: 44 | best global fitness (cost): 0.0087851

Iteration: 45 | best global fitness (cost): 0.0087851

Iteration: 46 | best global fitness (cost): 0.0068151

Iteration: 47 | best global fitness (cost): 0.0068151

Iteration: 48 | best global fitness (cost): 0.0068151

Iteration: 49 | best global fitness (cost): 0.0068151

OPTIMUM SOLUTION

> [0.9965802, 3.0395979]

OPTIMUM FITNESS

> 0.0068151

Now, in case you want to plot the fitness value for each iteration, then set plot=True (here Tmax=50 is the maximum iteration)

>>> CSO(fitness=fitness\_2, Tmax=50, plot=True).execute()

You will see the following similar output:

OPTIMUM SOLUTION

> [0.9965802, 3.0395979]

OPTIMUM FITNESS

> 0.0068151

References:

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