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Improved Horse Herd Optimisation with Backtracking Search Algorithm

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Outline

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Mathematical Optimization

- It refers to the process of finding the optimal value of a system’s state within given bounds of state variables and often under a set of constraints.

- In almost all cases, a mathematical formulation for the problem is needed, given by an objective function, bounds of decision variables and mathematical description of constraints.

- It has applications in fields like mechanics, economics and finance, and machine learning.

Metaheuristics

- They are a type of algorithms which can only communicate the fitness value of a proposed solution with the outside world. They don’t have any knowledge about, say, the objective function’s behaviour .
- In almost all cases, a mathematical formulation for the problem is needed, given by an objective function, bounds of decision variables and mathematical description of constraints.
- They can’t guarantee global optimality but are quite easy to use, even on higher dimensional problems, and are thus preferred over classical optimization techniques in real-life scenarios, which are quite complex.

Horse-herd Optimization Algorithm

- Horse herd optimization algorithm is a swarm intelligence based algorithm focused on solving higher-dimensional problems. It is similar to PSO in this regard.

- Based on the behaviour of horses in herds. Population resembles a herd of horses. The whole population is divided into four groups, resembling different age groups.

- The youngest horses are the most adventurous ones, supporting global exploration, and for older horses, they limit their movement and instead aid in local exploitation.

- Horses depict social behaviours like imitation, defense, roam, grazing, hierarchy and sociability. These traits are mimicked my velocities of different kinds.

Limitations of HOA

- On some problems, HOA seems to suffer from a lack diversity in population as the iterations go on. This reduces its global exploration capability and results in poor performance and sub-optimal values.

- This premature convergence can be avoided by increasing the diversity of population.

- So now we look at another algorithm, BSA, that offers this exact advantage, i.e., global exploration capability.

Backtracking Search Optimization

- Backtracking Search optimization is an evolutionary algorithm, which are based on the principles of evolution (first proposed by Charles Darwin).

- A mutant is generated from the current and an old population, and then the final form of the trial population is generated by crossover.

- The mix rate parameter in the BSA's mutation process controls the numbers of elements of individuals that will mutate in a trial. The function of the mix rate is different from the crossover rate used in DE.

- Finally, the population is updated using a one-to-one greedy selection

BSA Advantages & Neighbourhoods

- BSA has a high global exploration tendency, which comes about due to the mutation & crossover operations, along with a memory element in the form of old population

- These ideas have been borrowed in order to improve the performance of HOA.

- However, BSA also has a tendency to suffer from slow convergence. So in order to counteract this, we also introduce the concept of neighbourhoods.

- Each horse belongs to a particular neighbourhood, and each neighbourhood has a locally optimum solution.

Neighbourhoods

- This was an idea proposed in an improved Particle Swarm Optimization paper, but was discussed in brief.

- Horses tend to move in small groups within a large herd.

- It is implemented by dividing the population into small neighbourhoods, each of equal size and each horse being randomly assigned to a neighbourhood.

- Using the local best solution in place of personal best increases convergence rate.

Modified HOA

- This proposed modification attempts to solve the problem with global explorability by using the aforementioned concepts of mutation/crossover and neighbourhoods.

- The concept of memory allows the current generation to learn from the experience of the previous generations, and may help in avoiding worse solutions.

- The number of functional evaluations, which were Np*T + Np, increase by Np for the same number of iterations. This increase is negligible in case of large number of iterations compared to population size.

Comparison between m-HOA and HOA

- The algorithm showed considerable improvement in performance on a number of benchmark problems

- Performance became more sensitive to damping ratio parameter in m-HOA, in contrast to the original algorithm.

- The proposed algorithm, due to the computational cost of the mutation/crossover operations requires significantly more time, for the same number of operations.

Functions	Equation	Range	Optimum	HOA	m-HOA
Colville (4D)	$100(x_1^2-x_2)^2+(x_1-1)^2+(x_3-1)^2+90(x_3^2-x_4)^2$ $+10.1((x_2-1)^2+(x_4-1)^2)+19.8(x_2-1)(x_4-1)$	[-10,10]	0		
mean				3.60286818	2.41188E-08
Std Dev.				1.879463881	3.95303E-08
Best				1.13360479	9.87501E-13
Easom (10D)	$(-1)^d\Big(\prod_{i=1}^{d}\cos^2(x_i)\Big)exp\Big[-\sum_{i=1}^{n}(x_i-\pi)^2\Big]$	$[-2\pi,2\pi]$	-1		
Mean				-0.806581902	-0.999999032
Std Dev.				0.222460132	3.06154E-06
Best				-0.992035093	-1
Easom (30D)	$(-1)^d\Big(\prod_{i=1}^{d}\cos^2(x_i)\Big)exp\Big[-\sum_{i=1}^{n}(x_i-\pi)^2\Big]$	$[-2\pi,2\pi]$	-1		
Mean				0	-0.999980367
Std Dev.				0	3.92819E-05
Best				0	-1
Michalewicz (5D)	$-\sum_{i=1}^{d}sin(x_i)sin^{2m}(\frac{ix_i^2}{\pi})$	$[0,\pi]$	-4.6876858		
Mean				-4.286189212	-4.687658179
Std Dev.				0.333750196	5.88759E-13
Best				-4.60049743	-4.687658179
Michalewicz (10D)	$-\sum_{i=1}^{d}sin(x_i)sin^{2m}(\frac{ix_i^2}{\pi})$	$[0,\pi]$	-9.66015		
Mean				-6.269095049	-9.599316075
Std Dev.				0.801561365	0.064423606
Best				-7.32810833	-9.660151716
Modified Langermann (10D)	$-\sum_{i=1}^{m}\Big(c_j cos(d_j/\pi)exp(-\pi d_j)\Big), d_j=\sum_{j=1}^{d}(x_j-A_{ij})^2$	[0, 10]	-0.965		
Mean				-0.307374374	-0.57070765
Std Dev.				0.288497726	0.262807503
Best				-0.7053177550	-0.705525179
Perm Function (D, beta) (2D)	$\sum_{i=1}^{d}\Big(\sum_{j=1}^{d}(j_i+\beta)\Big(\Big(\frac{x_j}{j}\Big)^i-1\Big)\Big)^2$	[-2,2]	0		
Mean				1.76073E-06	0
Std Dev.				3.0663E-06	0
Best				3.30396E-10	0
Perm Function (D, beta) (5D)	$\sum_{i=1}^{d}\Big(\sum_{j=1}^{d}(j_i+\beta)\Big(\Big(\frac{x_j}{j}\Big)^i-1\Big)\Big)^2$	[-5,5]	0		
Mean				317.1697127	0.109338151
Std Dev.				400.3182494	0.15936805
Best				31.59208796	0.0041797
Perm Function (0, D, beta) (5D)	$\sum_{i=1}^{d}\Big(\sum_{j=1}^{d}(j+\beta)(x_j^i-\frac{1}{j^i})\Big)^2$	[-5,5]	0		
Mean				6.924621745	0.025707552
Std Dev.				3.13278806	0.046759022
Best				2.111677761	3.15448E-07

Functions	Equation	Range	Optimum	HOA	m-HOA
Power Sum (4D)	$\sum_{i=1}^{d}\left[\left(\sum_{j=1}^{d} x_j^i\right)-b_i\right]^2$	[0,4]	0		
Mean				0.239616435	0.002328661
Std Dev.				0.249090057	0.003793212
Best				0.072680439	5.87414E-06
Rosenbrock (5D)	$\sum_{i=1}^{d-1}\left[100(x_{i+1}-x_i^2)^2+(x_i-1)^2\right]$	[-5,10]	0		
Mean				3.33354967	0.000994324
Std Dev.				0.957161174	0.001327506
Best				1.48114315	5.05419E-07
Rosenbrock 2.0 (30D)	$\sum_{i=1}^{d-1}\left[100(x_i+1-x_i^2)^2+(x_i-1)^2\right]$	[-5,5]	0		
Mean				1501.152528	43.41484831
Std Dev.				98.40209302	8.94276239
Best				1327.530228	28.90789221
Schwefel (5D)	$418.9829d-\sum_{i=1}^{d} x_i sin(\sqrt{\lvert x_i \rvert})$	[-500,500]	0		
Mean				166.1823141	0.000358547
Std Dev.				119.9843864	0.000931914
Best				38.75635797	6.36378E-05
Shekel (4D)	$-\sum_{i=1}^{m}\left(\sum_{j=1}^{4}(x_j-C_{ji})^2+\beta_i\right)^{-1}$	$[0, 10]$	-10.5364		
Mean				-9.684084761	-9.243129822
Std Dev.				1.799734073	2.726543903
Best				-10.4727897	-10.53644315
Styblinski Tang (10D)	$\frac{1}{2}\sum_{i=1}^{d}(x_i^4-16x_i^2+5x_i)$	$[-5, 5]$	-391.6599		
Mean				-371.5254763	-391.661657
Std Dev.				23.46239407	0
Best				-388.1531958	-391.661657
Styblinski Tang (100D))	$\frac{1}{2}\sum_{i=1}^{d}(x_i^4-16x_i^2+5x_i)$	$[-5, 5]$	-3916.599		
Mean				-2111.188834	-3907.598602
Std Dev.				82.16151967	7.129719273
Best				-2255.343651	-3915.910163
Trid (10D)	$\sum_{i=1}^{d}(x_i-1)^2-\sum_{i=2}^{d}(x_i x_{i-1})$	$[-100, 100]$	-210		
Mean				-1.154766703	-209.99999448
Std Dev.				12.80878943	1.20644E-05
Best				-34.56815121	-210
Trid (20D)	$\sum_{i=1}^{d}(x_i-1)^2-\sum_{i=2}^{d}(x_i x_{i-1})$	$[-400, 400]$	-1520		
Mean				11.81613462	-1500.935659
Std Dev.				4.990207401	15.84016939
Best				-0.79409643	-1517.220452

Conclusion

- The proposed approach works significantly better on a number of benchmark functions.

- In spite of such performance there is further room for improvement, especially in tackling the time complexity aspect of the approach.

- On certain benchmarks functions such as sphere and Rastrigin, HOA’s performance was better.