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Improved coati optimization algorithm through multi-strategy integration: from theoretical design to engineering applications

Shuangxi LIU, Ruizhe FENG, Yuxin WEI, Wei HUANG, Binbin YAN

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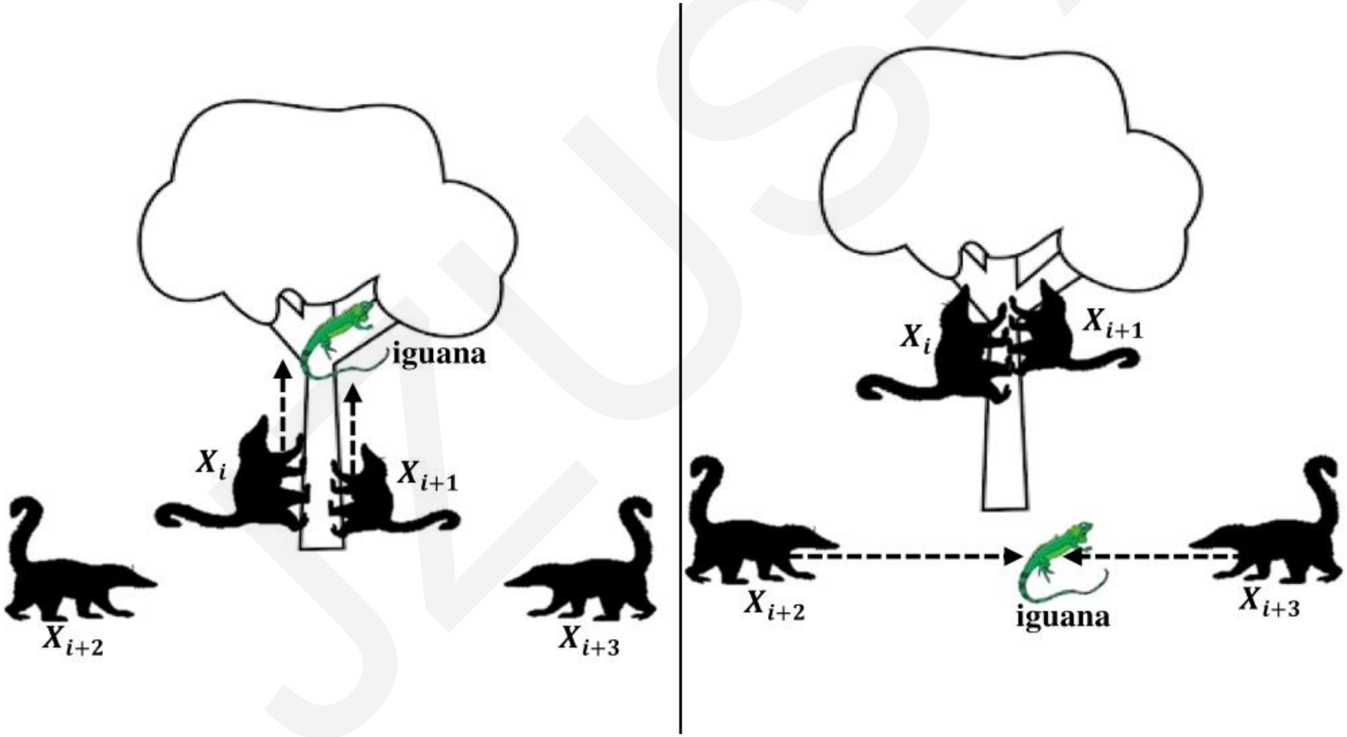
Background

- Swarm intelligence algorithms have garnered significant attention among heuristic algorithms due to their capacity to emulate the collective behavior observed in natural organisms. Despite the significant achievements of swarm intelligence algorithms, ongoing research has revealed several limitations inherent to these methods.

- These limitations include a tendency to fall into local optima, slow convergence speeds, and difficulty in parameter adjustment. Consequently, enhancing the performance and effectiveness of swarm intelligence algorithms, either through development of new algorithms or refinements to existing ones, has become a prominent research area in recent years.

Background

The coati optimization algorithm (COA) is a novel swarm intelligence optimization technique inspired by the foraging behavior of South American coatis, known for their complex group cooperation and highly social nature.



Description of the COA

Background

Although COA has demonstrated advantages over other typical swarm intelligence algorithms in solving optimization problems, it also faces two significant limitations.

1. COA suffers from a lack of population diversity. The random generation of the initial population may result in insufficient diversity, which can impede the algorithm’s capacity to effectively explore the solution space.

2. COA is prone to becoming stuck in local optima. Like many heuristic algorithms, COA may experience a slowdown in convergence speed and is susceptible to becoming trapped in local optima.

Methods

To address the aforementioned limitations of COA, we integrate three strategies: Latin hypercube sampling (LHS), Lévy-flight, and adaptive local search, and accordingly propose an improved coati optimization algorithm (ICOA).

1. In the population initialization phase of the ICOA, LHS is introduced to enhance sample uniformity and minimize redundancy.

2. In the exploration phase, the integration of the Lévy flight strategy into ICOA significantly enhances the algorithm's global search capability.

3. During the exploitation phase of ICOA, an adaptive local search strategy is introduced to enhance performance.

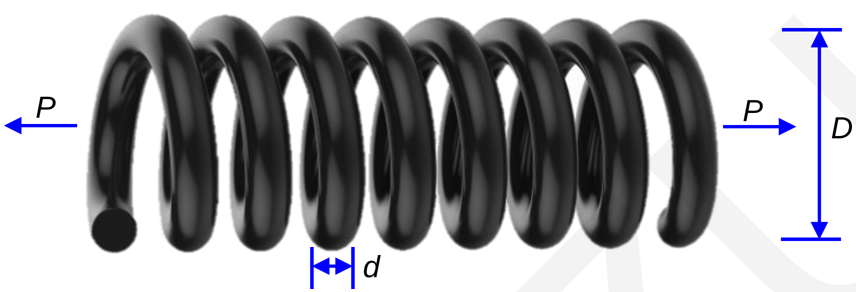
Results

This study employs 12 benchmark functions for performance testing.

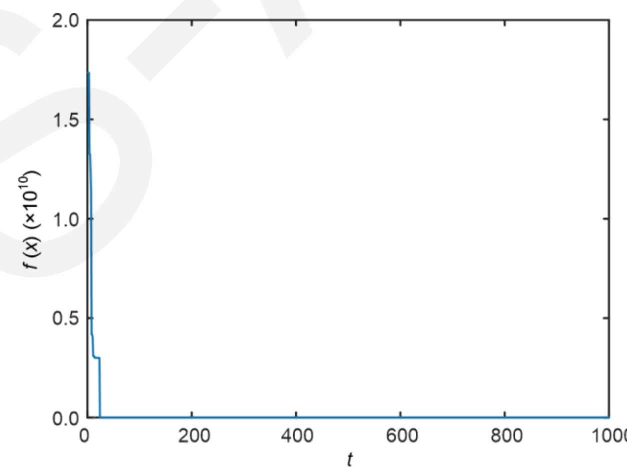
Function	Range	Dimension	Optimal value
$\mathcal{F}_1(x) = \sum_{i=1}^{n} x_i^2$	[-100,100]	30	0
$\mathcal{F}_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[-10,100]	30	0
$\mathcal{F}_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	[-100,100]	30	0
$\mathcal{F}_4(x) = \max_i \left[\lvert x_i \rvert, 1 \leq i \leq n \right]$	[-100,100]	30	0
$\mathcal{F}_5(x) = \sum_{i=1}^{n-1} \left\{ 100 \left(x_{i+1} - x_i^2 \right)^2 + (x_i - 1)^2 \right\}$	[-30,30]	30	0
$\mathcal{F}_6(x) = \sum_{i=1}^{n} (x_i + 0.5)^2$	[-100,100]	30	0
$\mathcal{F}_7(x) = \sum_{i=1}^{n} i x_i^4 + \text{random}(0,1)$	[-1.28,1.28]	30	0
$\mathcal{F}_8(x) = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert} \right)$	[-500,500]	30	-12569.5
$\mathcal{F}_9(x) = \sum_{i=1}^{n} \left[x_i^2 - 10\cos(2\pi x_i) + 10 \right]$	[-5.12,5.12]	30	0
$\mathcal{F}_{10}(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n} \cos(2\pi x_i) \right) + 20 + \exp$	[-32,32]	30	0
$\mathcal{F}_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}} \right) + 1$	[-600,600]	30	0
$\mathcal{F}_{12}(x) = \frac{\pi}{n}\left\{ 10\sin(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 \left[1 + 10\sin^2(\pi y_{i+1}) \right] + (y_n - 1)^2 \right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}, u(x_i, k, a, m) = \begin{cases} k(x_i - a)^m, x_i > a \\ 0, -a < x_i < a \\ k(-x_i - a)^m, x_i < -a \end{cases}$	[-50,50]	30	0

Results

Moreover, this study focuses on assessing the applicability and advantages of ICOA through testing on the tension/compression spring design problem.



Tension/compression spring design



Convergence process of ICOA applied to the tension/compression spring design problem

The simulation results demonstrate that ICOA exhibits superior optimization performance on a tension/compression spring design problem compared to seven other swarm intelligence algorithms.

Conclusions

1. The integration of LHS, Lévy-flight distribution, and adaptive local search strategies significantly enhanced both the quality and diversity of the population, thereby improving the algorithm's performance.

2. The proposed ICOA was tested using 12 benchmark functions, with its performance compared to traditional optimization algorithms including COA, PSO, ALO, GWO, and MFO. Analysis of convergence, stability, and statistical significance was performed, as assessed through the Wilcoxon rank sum test.

3. The practical applicability and efficacy of the ICOA have been substantiated through successful application on design optimization of tension/compression springs.