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Hybridization Approach for Ant Lion Optimizer (ALO) using Particle Swarm Optimization (PSO)

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Abstract
Optimization algorithms are essential for addressing intricate real-world challenges by effectively identifying optimal or near-optimal solutions. The Ant-lion Optimization Algorithm (ALO) has proven to be effective in various optimization scenarios; however, its performance can often be enhanced through hybridization with other meta-heuristic methods. This research examines the effects of integrating Particle Swarm Optimization (PSO) with the ALO algorithm by contrasting the results obtained from the original ALO with those from the hybridized approach. The efficacy of the hybrid method was assessed using a range of benchmark functions (F1 to F23), which encompass various optimization problems, including uni-modal, multi-modal, and fixed-point functions. The findings indicate that the PSO-ALO hybridization significantly boosts optimization performance for several functions, such as F1, F3, F6, F7, and F9, where the function values showed a notable decrease, reflecting improved solution accuracy and convergence rates.

Keywords: Hybridization, PSO, Nature-Inspired Algorithms, Benchmark, Meta-heuristic Optimization.

1. Introduction

Optimization plays a crucial role in solving complex real-world problems by efficiently identifying optimal or near-optimal solutions. Various meta-heuristic algorithms have been developed to tackle such challenges, among which the Ant-lion Optimization Algorithm (ALO) has gained attention for its strong optimization capabilities. However, despite its effectiveness, ALO can sometimes face limitations, such as slow convergence or getting trapped in local optima. To overcome these drawbacks, researchers have explored hybridization techniques, where ALO is combined with other optimization methods to enhance its overall performance.

One promising hybrid approach involves integrating Particle Swarm Optimization (PSO) with ALO. PSO is well known for its ability to quickly explore solution spaces and improve convergence speed, making it a suitable complement to ALO's search mechanism. By combining these two techniques, it is possible to leverage their strengths while mitigating individual weaknesses. This study examines the impact of PSO-ALO hybridization by comparing the results obtained using the original ALO algorithm with those achieved through the hybrid method.

This work proposed a novel nature-inspired algorithm called ALO. The hunting behavior of ant-lions and entrapment of ants in ant-lions traps were the main inspirations for this algorithm. Several operators were proposed and mathematically modeled for equipping the ALO algorithm with high exploration and exploitation. After the survey it was observed by comparing both original values and hybridization values results was very impressive. An optimization-based method was proposed in this paper for the problem of

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instance reduction to obtain better results in terms of many metrics in both balanced and imbalanced data. A new modified ant-lion optimization (MALO) method was adapted for this task after validating its ability in terms of optimization compared to state-of-the-art optimizers using benchmark functions. The results obtained at 500 and 1000 iterations for twenty-three and thirteen benchmark functions, respectively, demonstrated that the proposed MALO algorithm could escape the local optima and provide a better convergence rate as compared to the basic ALO algorithm and state-of-the-art optimizers.

Additionally, instance reduction results from MALO were compared to basic ant-lion Optimization and some well-known optimization algorithms on 15 balanced and imbalanced datasets to test the performance on reducing instances of the training data. Furthermore, ant-lion optimization and MALO were used to perform training data reduction for 18 over-sampled imbalanced datasets, and the reduced datasets were classified by SVM in all experiments. The results were also compared with one novel resampling method.

2. Mathematical Expression of Pso

Table.1. Standard Benchmark Functions

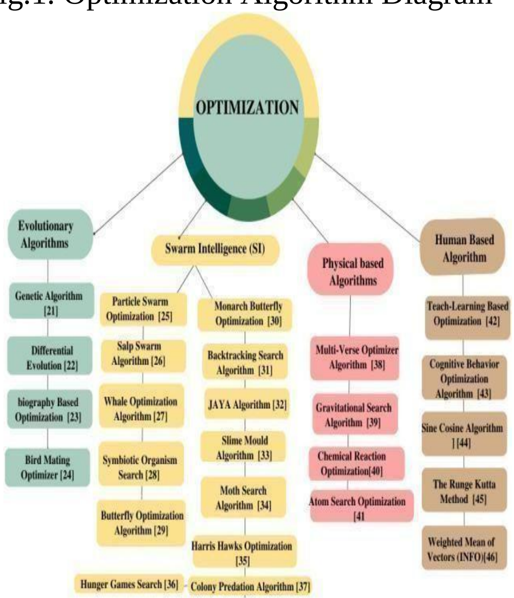
Table 2: Standard UM benchmark functions

Functions	Dimensions	Range	f_{min}
$F_1(S) = \sum_{m=1}^{z} S_m^2$	(10,30,50,100)	[-100 , 100]	0
$F_2(S) = \sum_{m=1}^{z} \lvert S_m \rvert + \prod_{m=1}^{z} \lvert S_m \rvert$	(10,30,50,100)	[-10 ,10]	0
$F_3(S) = \sum_{m=1}^{z} (\sum_{n-1}^{m} S_n)^2$	(10,30,50,100)	[-100 , 100]	0
$F_4(S) = max_m \{\lvert S_m \rvert, 1 \le m \le z\}$	(10,30,50,100)	[-100 , 100]	0
$F_5(S) = \sum_{m=1}^{z-1} [100(S_{m+1} - S_m^2)^2 + (S_m - 1)^2]$	(10,30,50,100)	[-38 , 38]	0
$F_6(S) = \sum_{m=1}^{z} ([S_m + 0.5])^2$	(10,30,50,100)	[-100 , 100]	0
$F_7(S) = \sum_{m=1}^{z} m S_m^4 + random\ [0,1]$	(10,30,50,100)	[-1.28, 1.28]	0
Functions	Dimension	Range	f_{min}
$F_8(S) = \sum_{m=1}^{z} - S_m \sin(\sqrt{\lvert S_m \rvert})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z} [S_m^2 - 10\cos(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp(-0.2\sqrt{(\frac{1}{z}\sum_{m=1}^{z} S_m^2)}) - exp(\frac{1}{z}\sum_{m=1}^{z} \cos(2\pi S_m)) + 20 + e$	(10,30,50,100)	[-32,32]	0
$F_{11}(S) = 1 + \sum_{m=1}^{z} \frac{S_m^2}{4000} - \prod_{m=1}^{z} \cos\frac{S_m}{\sqrt{m}}$	(10,30,50,100)	[-600, 600]	0
$F_{12}(S) = \frac{\pi}{z}\{10\sin(\pi r_1) + \sum_{m=1}^{z-1}(r_m - 1)^2[1 + 10\sin^2(\pi r_{m+1})] + (r_z - 1)^2\} + \sum_{m=1}^{z} u(S_m, 10, 100, 4)$, $r_m = 1 + \frac{S_m + 1}{4}$, $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(10,30,50,100)	[-50,50]	0
$F_{13}(S) = 0.1[\sin^2(3\pi S_m) + \sum_{m=1}^{z}(S_m - 1)^2[1 + \sin^2(3\pi S_m + 1)] + (x_z - 1)^2[1 + \sin^2 2\pi S_z)]$	(10,30,50,100)	[-50,50]	0
Functions	Dimensions	Range	f_{min}
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{25} \frac{1}{n + \sum_{m=1}^{2}(S_m - b_{mn})^6}]^{-1}$	2	[-65.536, 65.536]	1
$F_{15}(S) = \sum_{m=1}^{11} [b_m - \frac{S_1(a_m^2 + a_m S_2)}{a_m^2 + a_m S_3 + S_4}]^2$	4	[-5, 5]	0.00030
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1S_2 - 4S_2^2 + 4S_2^4$	2	[-5, 5]	-1.0316
$F_{17}(S) = (S_2 - \frac{5.1}{4\pi^2}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1 - \frac{1}{8\pi})\cos S_1 + 10$	2	[-5, 5]	0.398
$F_{18}(S) = [1 + (S_1 + S_2 + 1)^2(19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1S_2 + 3S_2^2)] \times [30 + (2S_1 - 3S_2)^2(18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1S_2 + 27S_2^2)]$	2	[-2,2]	3
$F_{19}(S) = -\sum_{m=1}^{4} d_m exp(-\sum_{n=1}^{3} S_{mn}(S_m - q_{mn})^2)$	3	[1, 3]	-3.32
$F_{20}(S) = -\sum_{m=1}^{4} d_m exp(-\sum_{n=1}^{6} S_{mn}(S_m - q_{mn})^2)$	6	[0, 1]	-3.32
$F_{21}(S) = -\sum_{m=1}^{5} [(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0,10]	-10.1532
$F_{22}(S) = -\sum_{m=1}^{7} [(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.4028
$F_{23}(S) = -\sum_{m=1}^{7} [(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.5363

3. Literature Review

Ants which consider as candidate solutions move randomly in search of food which is optimal solutions. Their movements were modeled using random walk functions. On the other side there are ant-lions which are dig cone shaped pit in the sand. As soon as ant falls into the pits ant-lion throw sand to trap them. Then the best ant-lion i.e. solutions are continuously updated to ensure that the algorithm finds optimal solution. After that once the ant falls into the pit , the ant-lion pulls and consumes it i.e. it will keep repeating the solution till it reaches the optimize level means it gives proper solution of complex problems by repeating it multiple times until the best solution is found. As this algorithm results was very impressive.

Fig.1. Optimization Algorithm Diagram



Nature-inspired algorithms are widely used for solving complex optimization problems in engineering, computer science, bio-informatics, and machine learning. They can handle large search spaces and nonlinear problems where traditional algorithms struggle. Strong Balance between exploration and exploitation for NIAs incorporate both exploration (global search) and exploitation

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(local refinement) mechanisms, allowing them to escape local optima and high-quality solutions.

Nature-inspired algorithms provide efficiency, flexibility and adaptability for solving complex optimization problems. Their biological and natural inspirations make them an exciting field for research with continuous advancements real-world problem-solving.

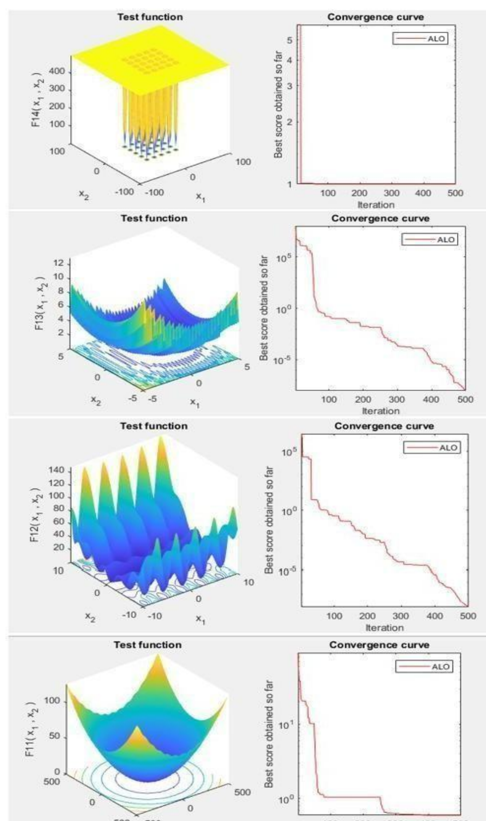
Table.2. Algorithms and its Authors

Algorithm No.	Algorithm Name	Author Name	Year
1.	Hybrid Ant Lion Mutated Ant Colony Optimizer Technique With Particle Swarm Optimization for Leukemia Prediction Using Microarray Gene Data	T. R. Mahesh, (senior member ,IEEE), D.Santhakumar, A.Balajee , H.S.Shreenidhi , V.Vinoth Kumar , (Member, IEEE), and Jonnakuti Rajkumar Annand	2024
2.	The Ant Lion Optimizer	S.Mirjalili	2015
3.	A comprehensive survey on the ant lion optimizer, variants and applications	V. Pathak, S.Gangwar, Ramanpreet Singh, A.Srivastava, Mithilesh K. Dikshit	2022
4.	A genetic operators-based Ant Lion Optimizer for training a medical multi-layer perceptron	M.Rojas, A.Olivera, P.Vidal	2023
5.	Optimal real power rescheduling of generators for congestion management using a novel ant lion optimizer	S.Verma, V.Mukherjee	2016

4. Result and Discussion

Obtained results demonstrated that the proposed MALO was superior in minimizing the number of training set instances, hence maximizing the classification performance while reducing the run time compared to state-of-the-art methods used to reduce the original balanced and imbalanced datasets without the need to perform oversampling pre-processing methods which consume computational time and memory space. MALO reduced the instances of over-sampled imbalanced datasets with better performance compared to the full over-sampled data set and the recently proposed ACOR instance reduction method, ALO, GWO, and WOA.

Fig.2. Results of Benc hmarks Functions



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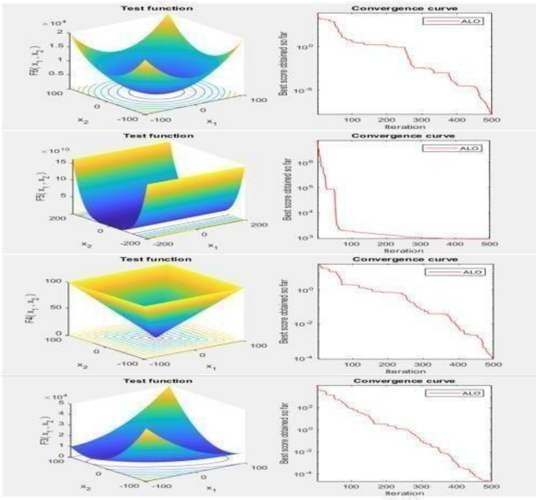

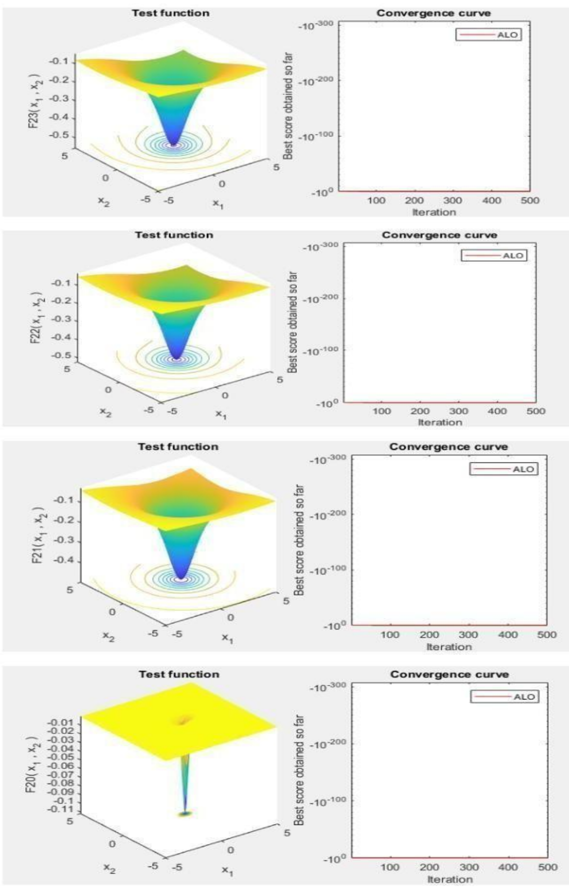

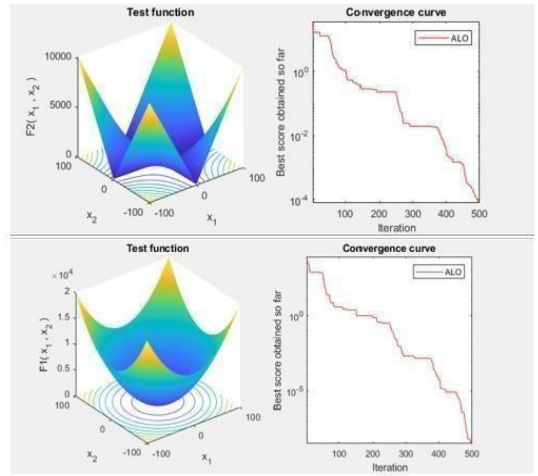

Function Name	Original Value	Hybridization Value
F1	5.79E-09	2.54E-10
F2	1.62E-05	0.000536953
F3	0.00022096	2.23E-09
F4	0.001360764	0.006122993
F5	6.842285022	0.088685109
F6	3.03E-09	4.15E-12
F7	0.025512477	0.009978113
F8	-1925.84698	-2729.054058
F9	22.88401797	11.93950365
F10	3.37E-05	1.155148503
F11	0.590579448	0.901583657
F12	0.311243232	2.10E-11
F13	2.34E-09	0.047522746
F14	0.998003838	0.998003838
F15	0.02076445	0.000307486
F16	-1.03162845	-1.031628453
F17	0.397887358	0.397887358
F18	3	3
F19	-3.86278215	-3.862782148
F20	-3.2030452	-3.321995172
F21	-5.10077214	-5.10077214
F22	-5.08767183	-2.751933564
F23	-10.5364098	-3.835426803

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5. Conclusion

The performance of this hybrid approach was tested across 23 benchmark functions (F1 to F23), which cover different types of optimization challenges, including uni-modal, multi-modal, and fixed-point problems. The results indicate that for certain functions, such as F1, F3, F6, F7, and F9, the hybrid algorithm significantly improved accuracy and convergence speed by reducing function values. Additionally, function F8 showed better minimization performance after hybridization.

However, the hybrid approach did not lead to improvements in all cases. In functions like F2, F4, F5, F10, F11, F13, and F22, the function values increased, indicating a decline in performance compared to the standalone ALO method. Moreover, some functions, such as F14, F16, F17, F18, F19, and F21, remained unchanged, suggesting that ALO had already reached optimal or near-optimal solutions, making hybridization unnecessary.

These findings highlight that while PSO-ALO hybridization can enhance optimization performance for many problems, it is not universally superior to standalone. The effectiveness of hybridization depends on the characteristics of the function being optimized. Therefore, future research should focus on developing adaptive hybridization techniques that can dynamically adjust the influence of PSO and ALO based on the nature of the problem. Such approaches could help achieve more consistent improvements across a wider range of optimization challenges.

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