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Hybridizing Polar Lights Optimizer with Particle Swarm Optimization for Improved Convergence in Real-World Applications

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Abstract
A new approach in the field of optimization, by Hybridization of Polar Lights Optimizer and Particle Swarm Optimization Algorithm too improve the performance for solving real-world complex applications. The Polar Light Optimizer Algorithm inspired by the behaviour of light in polar coordinates, is combines with The Particle Swarm Optimization Algorithm, which mimics the social behaviour of particles to explore the search space. In this paper the Proposed Hybrid approach seeks to improve convergence rate and solution accuracy, making it more efficient for handling high-dimensional, nonlinear and multimodal optimization problems. The Algorithms performance is assessed with 23(twenty-three) benchmark test functions, which shows the resilience and effectiveness in locating the best and optimal solutions.

Keywords: Optimization, Hybridization, Benchmark, Convergence, PLO, PSO

1. Introduction

Optimization Algorithm is crucial for solving complex problems across various fields, such as Engineering, Machine learning, and Data Analysis. The Polar Light Optimizer and Particle Swarm Optimization Algorithm have gained significant recognition due to their effectiveness in navigating large, high-dimensional work spaces.

Particle Swarm Optimization (PSO) is renowned for its ease of use and capacity to effectively search the search space. It was inspired by the social behaviour of birds and fishes. Nevertheless, it occasionally has trouble converge to the global optimum and finetuning solutions, especially in multimodal optimization environment [3], [7], [8]. In contrast, the Polar Light Optimizer (PLO), which draws inspiration from the way light behaves in polar coordinates, has demonstrated promise in efficiency, and improving solution precision. Although PLO does well in terms of exploitation, but its capacity to break out of local optima is limited by a lack of variations during exploration stage [6].

Hence, this study suggests a novel hybrid strategy between PSO and PLO in order to overcome such constraints. The hybrid algorithm seeks to strike a compromise between exploration and exploitation by combining the local exploitation of PLO with the global exploration capabilities of PSO [9], [10], [12]. The proposed hybrid method will increase the accuracy and speed of convergence when locating global optima. This hybrid method is intended to address the difficulties presented by multimodal, high-dimensional, nonlinear optimization issues where local and global search are crucial. Through the 23(twenty-three) benchmark test cases and performance comparisons with the original standalone PSO and PLO algorithms, the proposed hybrid algorithm investigates the effectiveness of combination of PLO and PSO Algorithm [12].

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2. Proposed Optimization Algorithm

2.1 Algorithm Classification

The **Nature Based Algorithms** are classified in four main categories- Human based, Evolution based, Swarm based and Physics based.

1. The **Human based algorithms** are inspired by human abilities, learning and social behaviour, they mimic the decision-making abilities of human beings [11].
- Teaching-Learning-Based Optimization (TLBO)
- Group Search Optimization (GSO)

2. The **Evolution Based algorithms** are based on Darwin's theory of Evolution, in which the best people survive and procreate to provide better solutions over generations.
- Genetic Algorithm (GA)
- Differential Evolution (DE)

3. The **Swarm Based algorithm** simulate the collective intelligence of insects and animals working together to tackle challenges and solve complex problems.
- Particle Swarm Optimization (PSO)

4. The **Physics Based Algorithm** draw inspiration from physical principles and natural forces like gravity, electromagnetic, and thermodynamics.
- Gravitational Search Algorithm (GSA)

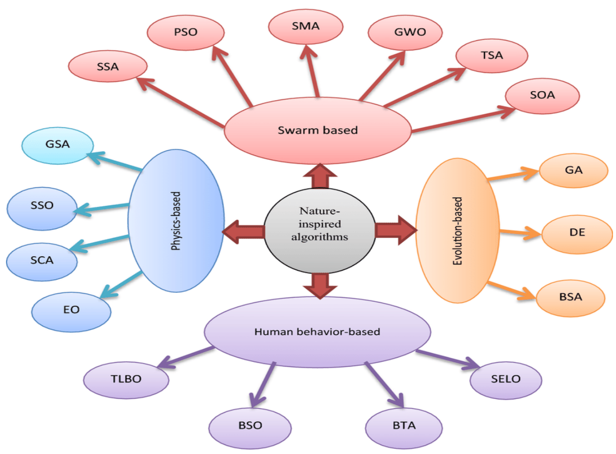

Figure1- Classification of Nature inspired Algorithms [18]

2.2 Classification Of Optimized Techniques

The Figure.1 presents a classification of Nature Inspired Algorithms, listing two algorithms each from Nature-Based, Human Behaviour-Based, Evolution-Based, and Swarm-Based Algorithm respectively. These Algorithms play a crucial role in solving complex optimization problems across various Real-world Applications [11].

2.3 Algorithms and Authors

The Table. 1 provides a compilation of prominent algorithms along with their respective authors, encompassing diverse optimization approaches such as Gravitational, Evolutionary, Swarm-Based, and Learning-Inspired techniques.

TABLE 1.

Number	Algorithm	Author
1	Gravitational Search Algorithm (GSA)	Rashedi, H. et al., (2009)
2	Simulated Annealing (SA)	Kirkpatrick, S. et al., (1983)
3	Teaching-Learning-Based Optimization (TLBO)	Rao, R. V. et al., (2011)
4	Brain Storm Optimization (BSO)	Shi, Y., (2011)
5	Genetic Algorithm (GA)	Holland, J. H., (1975)
6	Differential Evolution (DE)	Storn, R., Price, K., (1997)
7	Particle Swarm Optimization (PSO)	Kennedy, J., Ebarhart, R., (1995)
8	Ant Colony Optimization (ACO)	Dorigo, M. et al., (1991, 1996)

2.4.Pseudo-Code

The pseudo-code, which is based on real or natural event like particle interactions or aurora dynamics, describes an optimization technique that works on a high-energy particle cluster [6].

Parameters initializing: FEs=0, MaxFEs, t=0

Initialize high-energy particle cluster X.

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Calculate the fitness value f(X).
Sort X according to f(X).
Update the current optimal solution X_best.
While FEs<MaxFEs
Calculate the velocity v(t) for each particle, according to Eq. (12).
Calculate aurora oval walk Ao for each particle, according to Eq. (14).
Calculate weights W_1 and W_2 according to Eq. (17) and Eq. (18).
For each energetic particle do
Updating particles X_new using Eq. (16).
If r_4<K and r_5<0.05
Particle collision strategy: update particle X_new using Eq. (19).
End If
Calculate the fitness f(X_new).
FEs=FEs+1.
End For
If f(X_new)<f(X)
Iterating over X using the greedy selection mechanism.
End If
Sort X according to f(X).
Update the optimal solution X_best.
t=t+1.
End While
Return the X_best.

2.4 Mathematical Equations

TABLE 2.

$F_5(S) = \sum_{m=1}^{z-1}[100(S_{m+1}-S_m^2)^2 + (S_m-1)^2]$	(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
$F_7(S) = \sum_{m=1}^{z} mS_m^4 + random\,[0,1]$	(10,30,50,100)	[-1.28, 1.28]	0

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

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
$F_9(S) = \sum_{m=1}^{z}[S_m^2 - 10cos\,(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp\,(-0.2\sqrt{\left(\frac{1}{z}\sum_{m=1}^{z} S_m^2\right)}) - exp\,(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(10,30,50,100)	[-32,32]	0
$F_{11}(S) = 1 + \sum_{m=1}^{z}\frac{S_m^2}{4000} - \Pi_{m=1}^{z} cos\frac{S_m}{\sqrt{m}}$	(10,30,50,100)	[-600, 600]	0
$F_{12}(S) = \frac{\pi}{z}\left\{10\,sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m-1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z-1)^2\right\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_m+1}{4}$ $u(S_m,b,x,i) = \begin{cases} x(S_m-b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m-b)^i & S_m < -b \end{cases}$	(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}
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5\frac{1}{n+\sum_{m=1}^{z}(S_m-b_{mn})^6}]^{-1}$	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
$F_{17}(S) = (S_2 - \frac{5.1}{4\pi 2}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1-\frac{1}{8\pi})cosS_1 + 10$	2	[-5, 5]	0.398
$F_{18}(S) = \left[1+(S_1+S_2+1)^2\left(19-14S_1+3S_1^2-14S_2+6S_1S_2+3S_2^2\right)\right]\times \left[30+(2S_1-3S_2)^2\left(18-32S_1+12S_1^2+48S_2-36S_1S_2+27S_2^2\right)\right]$	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

2.5 Search Space

The set of all possible solutions of the proposed Hybridization PLO and PSO Algorithm that needs to be explored in order to find the optimal or near-optimal solution to the given problem. It establishes the parameters that the proposed algorithm works inside.

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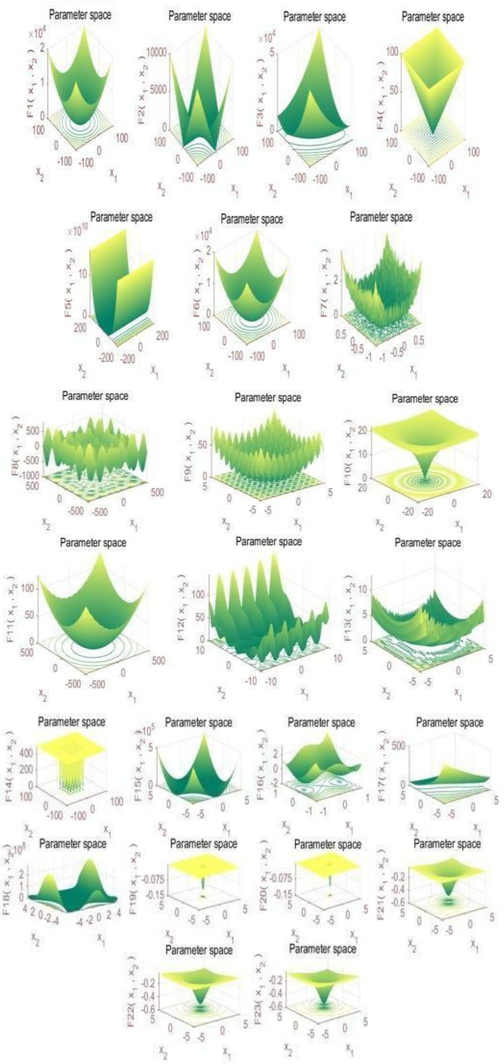

3 Result And Discussion

TABLE 3. Standard Benchmark Functions

Functions	Value of Original	Value of Hybridization
F1	0.0044604	1.44E-09
F2	0.032413	4.12E-06
F3	832.8044	192.7314
F4	0.6241	0.25629
F5	21.0004	12.9884
F6	0.0049052	4.77E-09
F7	0.060384	0.020343
F8	-10102.6324	-10191.6176
F9	26.9192	8.956
F10	0.017182	7.61E-06
F11	0.0089071	4.54E-09
F12	0.0075781	2.28E-09
F13	0.00044325	8.39E-10
F14	0.998	0.998
F15	0.00070342	0.00031416
F16	-1.0316	-1.0316
F17	-1.0476	-1.0476
F18	3	3
F19	-3.8628	-3.8628
F20	-3.322	-3.322
F21	-10.1531	-10.1532
F22	-10.4029	-10.4029
F23	-10.5363	-10.5364

The performance comparison between Polar Lights Optimizer and Particle Swarm Optimization Algorithm provides optimal solutions, when compared with the original Polar Lights Optimizer (PLO) Algorithm with an impressive result. The Hybrid approach achieved optimal results in F17(seventeen) out of 23(twenty-three) benchmark functions. In summary, The Hybridization of PLO and PSO Algorithm improves the optimization performance.

Conclusion

In Conclusion, a potential approach to resolve the optimization issue is the hybridization of PLO and PSO. The hybrid technique has the potential to provide significant improvements in convergence speed and solution accuracy. Hybridization results in Optimal solutions in Functions (F1, F2, F3, F4, F5, F6, F7, F8, F9, F10, F11, F12, F13, F15, F21, F23). Thus, the proposed hybrid of PLO and PSO algorithm showcases effectiveness in improving optimization performance.

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