A Hybridized Version of Crayfish Optimization Algorithm with Particle Swarm Optimization

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Abstract: The proposed algorithm is an improved version of Crayfish Algorithm. In this paper, a new hybrid model that integrates the Crayfish Optimization Algorithm (COA) and the Particle Swarm Optimization (PSO) for optimizing and increase performance. This hybrid algorithm being tested on 23 benchmarking functions, and the results indicate that the hybrid model is better than the individual Crayfish algorithm.
Keywords: Crayfish Optimization Algorithm (COA), Particle Swarm Optimization (PSO), Hybridization, Benchmark Functions, Optimization.

1. Introduction

Optimization plays a crucial role in various re alworld issues within sectors such as enginee ring, data science, and machine learning. In recent years, researchers have created many smart algorithms drawn from nature to address these issues more efficiently One of these algorithms is the Crayfish Optimization Algorithm (COA), inspired by the nature actions of crayfish, including their food-seeking behaviours, competition with others, and seasonal movements.

While COA is good at exploring different areas of the problem space (called **exploration**), it sometimes struggles to focus on the best solutions found so far (called **exploitation**). This can cause the algorithm to miss the best answers or take longer to find them.

To enhance this, we developed a hybrid algorithm that integrates COA with another popular technique known as PSO. PSO draws inspiration from the way birds mo ve in a flock and excels at rapidly enhancing existing solut ions. By combining COA's strong exploration with PSO's strong exploitation, our new algorithm aims to find better answers faster and more precisely. [3]

We tested the new COA-PSO hybrid on 23 benchmark functions and compared it with the original COA. The results show that the hybrid method gives better or equal performance in most cases. This proves that combining two algorithms work fast and give more optimize results.

In short, the proposed COA-PSO hybrid algorithm brings together the exploration strength of COA and the exploitation ability of PSO. This combination leads to improved performance in solving complex optimization problems, as shown by the results on benchmark test functions.

2. Proposed Optimization Algorithm

In this research, we select the Whale Optimization Algorithm (WOA) or Particle Swarm Optimization (PSO) hybridization because it delivers the impressive results by effectively balancing exploration and exploitation. This results in higher accuracy and faster convergence than using WOA or PSO individually.

PSO is great at quickly finding better answers by focusing on the best solutions. On the other hand, COA is good at exploring many different possibilities and avoiding getting stuck in the wrong place. When we combine them, PSO helps the algorithm move fast toward good solutions, while COA keeps exploring to make sure we don't miss the best one.

Classification of Algorithm:

Optimization techniques can be classified into four categories: nature-inspired, evolutionary, human-based, and physics-based algorithms.

https://doi.org/10.5281/zenodo.17452138

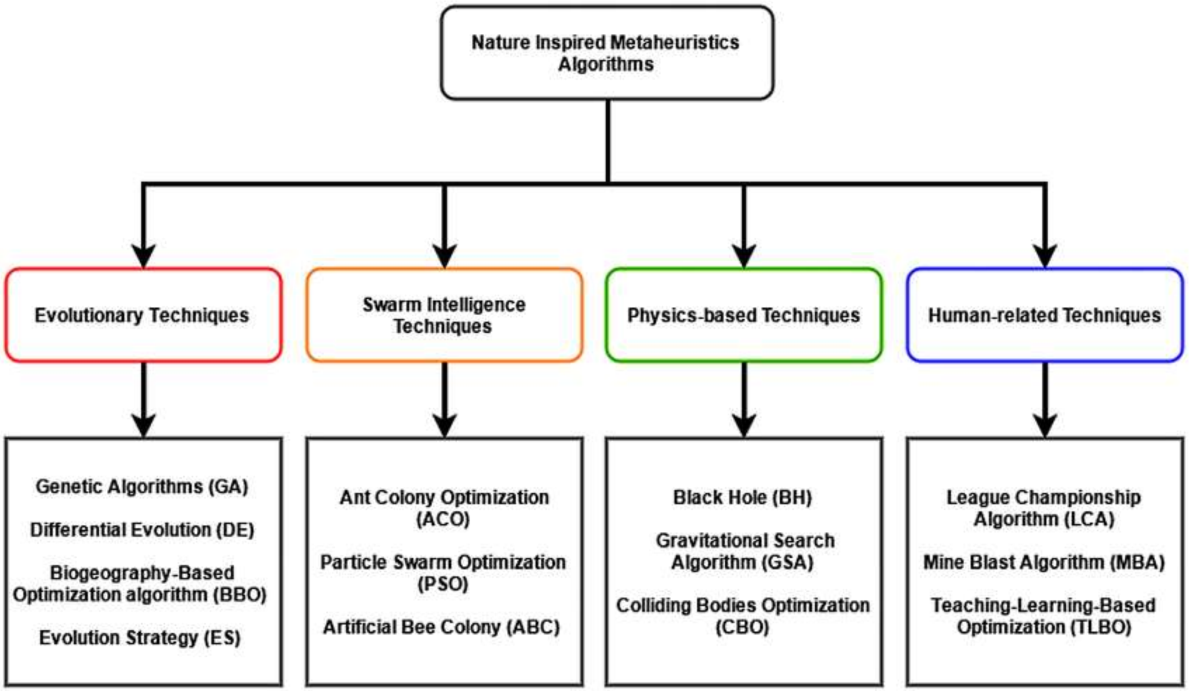


Fig-1: Classification of Algorithms [3]

The below table shows details of various meta-heuristics algorithm developed to solve complex optimization problem.

2.2 Classification of Optimization Techniques Table:

Table 1: Algorithm and Authors

Numbers	Algorithms	Author(s)	Year of Publication
1	Crayfish Optimization Algorithm (COA)	Seyedali Mirjalili et al	2023
2	Particle Swarm Optimization (PSO)	Kennedy & Eberhart	1995
3	Ant Colony Optimization (ACO)	Dorigo & Gambardella	1997
4	Artificial Bee Colony (ABC)	Karaboga et al.	2005
5	Simulated Annealing (SA)	Kirkpatrick et al.	1983
6	Gravitational Search Algorithm (GSA)	Rashedi et al.	2009
7	Teaching-Learning-Based Optimization (TLBO)	Rao et al.	2011
8	Social Spider Optimization (SSO)	Cuevas, Cienfuegos, Zaldívar et al.	2013

Tabel-1: Algorithm Details

2.3 Steps:

1. Obtained optimal values using the original Crayfish Optimization Algorithm (COA) on 23 benchmark functions.

2. Hybridized COA with Particle Swarm Optimization (PSO) to improve performance.
3. Performed multiple iterations for each benchmark function to test the hybrid algorithm.
4. Obtained optimal values using standalone PSO for comparison.
5. Compared the best solutions of COA and the hybrid COA-PSO approach.
6. Hybrid COA-PSO showed improved results in 15 out of 23 benchmark functions.

2.4 Benchmark Functions:

A benchmark function is a mathematical test used to
evaluate an algorithm's performance. Every f unction tests algorithms across various aspect s.

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
$F_4(S) = max_m\{\lvert S_m \rvert, 1 \leq m \leq z\}$	(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
$F_7(S) = \sum_{m=1}^{z} mS_m^4 + random\,[0,1]$	(10,30,50,100)	[-1.28, 1.28]	0
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\lvert S_m \rvert})$	(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
$F_{10}(S) = -20exp\,(-0.2\sqrt{(\frac{1}{z}\sum_{m=1}^{z} S_m^2)}) - exp\,(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(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

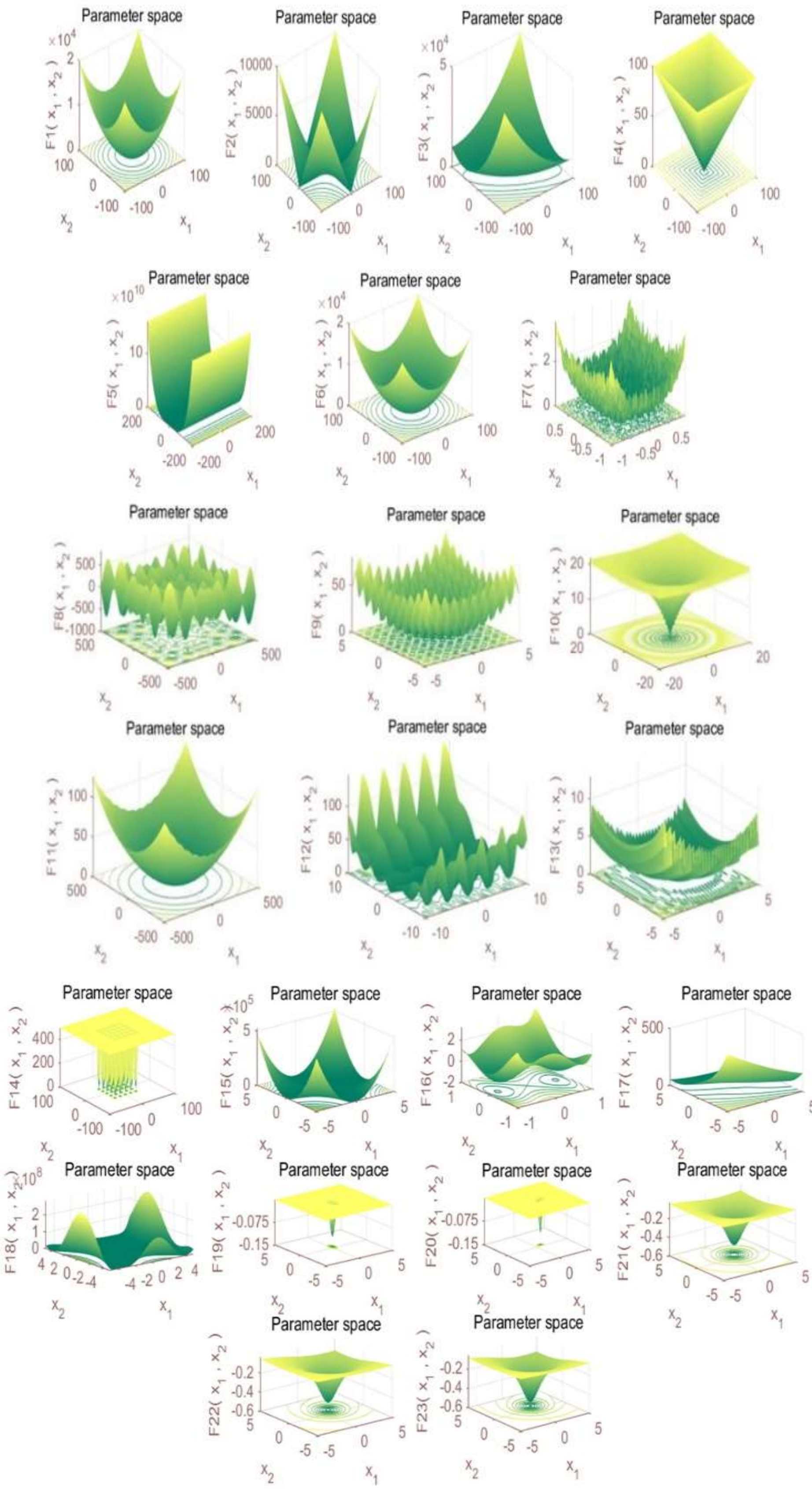
https://doi.org/10.5281/zenodo.17452138

$F_{12}(S) = \frac{\pi}{z}\left\{10\sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10\sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\right\} + \sum_{m=1}^{z} u(S_m, 10, 100, 4)$ $\tau_m = 1 + \frac{S_m + 1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(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
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5 \frac{1}{n + \sum_{m=1}^{z}(S_m - b_{mn})^6}]^{-1}$	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
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1 S_2 - 4S_2^2 + 4S_2^4$	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
$F_{18}(S) = \left[1 + (S_1 + S_2 + 1)^2(19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1S_2 + 3S_2^2)\right] \times \left[30 + (2S_1 - 3S_2)^2(18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1S_2 + 27S_2^2)\right]$	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

Tabel-2: Benchmark functions [6]

2.5 Search Space:

https://doi.org/10.5281/zenodo.17452138



https://doi.org/10.5281/zenodo.17452138

3. Results And Discussion

In the below table it shows the comparison between the Crayfish Optimization Algorithm (COA) and its Hybrid. The proposed algorithm being tested on 23 benchmark functions to determine its performance.

Table 3: Original and Hybrid Value

Function	Value of COA	Value of Hybrid
F1	0	0
F2	5.84E-182	2.81E-148
F3	0	0
F4	4.09E-200	7.18E-161
F5	6.4892	6.0659
F6	1.70E-06	3.19E-05
F7	1.75	1.70
F8	-3834.4211	-3994.8145
F9	0	0
F10	4.44E-15	4.44E-16
F11	0	0
F12	3.45E-06	6.77E-06
F13	0.10091	0.0016064
F14	2.0016	1.1081
F15	0.00030785	0.0007066
F16	-1.0316	-1.0317
F17	0.39789	0.39777
F18	3	3
F19	-3.8628	-3.8624
F20	-3.2031	-3.322
F21	-5.0552	-5.054
F22	-3.7243	-10.3869
F23	-10.5364	-10.5376

From above table, it concludes that hybrid COA-PSO provide more relevant and optimize value as compared to individual COA algorithm. The Hybrid approach was tested 23 times and performed better than the Crayfish Optimization Algorithm (COA) in most cases. Specifically, the Hybrid approach achieved better results in 11 out of 23.

4. Conclusion

In this study, the combined Crayfish Optimization Algorithm (COA) and Particle Swarm Optimization (PSO) was evaluated on 23 benchmark functions. The hybrid algorithm performed better than the original COA in 11 functions, namely F5, F7, F8, F10, F13, F14, F16, F17, F20, F22, and F23. It demonstrated equivalent performance in 5 functions, (F1, F3, F9, F11, F18), whereas the original COA was better in 7.

This indicates that the hybrid COA-PSO method works better for most of the test problems. It gives more accurate results, finds the best answers quickly and performs well even with difficult problems. This proves that combining the two algorithms enhance the optimization process more effective and reliable.

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