Integrating Artificial Hummingbird Algorithm with Particle Swarm Optimization for Enhanced Convergence and Accuracy

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Abstract
The Artificial Hummingbird Algorithm (AHA) is a bio-inspired optimization algorithm that simulates hummingbird foraging behavior.[1] The present study recommends a hybrid approach combining AHA with PSO algorithms for its improved convergence speed and solution quality. Experimentation shows the hybrid AHA performing better than the single AHA and other algorithms with better solution quality and stability for challenging problems of optimization[2]. In this paper author to optimize for enhanced convergence and accuracy in algorithm Artificial Hummingbird Algorithm with Particle Swarm Optimization.

Keywords— Intelligence, Benchmark, Algorithm, Hummingbird, Bio-inspired

I. Introduction

In the last decades, numerous optimization procedures have been created in order to solve an incredibly large number of optimization problems in many fields of application. Because of the continuous change of human society and industrial production, optimization tasks in reality became more complicated at one time[3]. As a result of additional complication, greater requirements were imposed on optimization techniques to look for even more sophisticated and cheaper mechanisms to generate the optimum solutions[1]. Geometric modeling is fundamentally concerned with the representation, approximation, analysis, and generation of surfaces and curves in computer imaging contexts. Geometric modeling addresses the construction of mathematical and computational models that capture the shape, structure, and geometry of geometric objects. Geometric modeling underlies computer graphics, computer-aided design (CAD), and 3D modeling, where handling curves and surfaces efficiently and accurately is paramount in the creation of realistic images, simulations, and virtual worlds[3]-[1].
Natural or biological process-inspired meta-heuristic optimization methods are efficient in avoiding local optima to achieve global solutions. They perform optimally in solving complex, high-dimensional, nonlinear problems like path planning, resource allocation, neural network optimization, optimal control, and parameter tuning[2][3].
Meta-heuristic optimization methods are particularly well-equipped to address decision-making problems of complexity, with non-linear, high-dimensional, and non-convex variables[1][3]. They are used in problem-solving in real life in other fields, such as path finding, where paths of navigation are minimized; resource scheduling, where resources are optimized for delivery; neural network search architecture, designing networks optimally to ensure[1].
The maximum performance; optimal control, where strategies maximize regulation within the system; and parameter estimation, where variables are adjusted to achieve maximum accuracy. Their flexibility and ability make

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them useful tools to address complex optimization problems in many applications[2].

The Artificial Hummingbird Algorithm (AHA) is a bio-inspired metaheuristic optimization algorithm that mimics the humming of hummingbird flight and its foraging mode to solve optimization problems[3]. The reason why it is different from traditional metaheuristic algorithms is because it possesses a new memory and biologically founded basis[3].

Bio-inspired algorithms have been a norm in meta-heuristic optimization, and they have gained much ground in the recent past. The algorithms imitate the behaviors and adaptive mechanisms of organisms and translate them into mathematical problems that solve complex problems efficiently[2]. Their ability to optimize solutions has earned them a favorite among the majority of engineering and computational fields. The sheer magnitude of the variety of nature's organisms is a source of perpetual inspiration for the development of new and efficient optimization techniques[1].

2. Literature Review

2.1.FoundationofDevelopmentandAlgoritm

AHA's development is a case of biomimicry, based on the intricate flight and foraging behavior of hummingbirds. The algorithm has been engineered to mimic their energy-efficient hovering, rapid reaction to motion, and territorial defense. AHA integrates behavioral modelling, mathematical descriptions, and a formal rigorous computational framework to improve optimization. The fundamental principles of AHA's structure allow it to explore complex search spaces effectively, and therefore it is a potential candidate for the solution of realistic optimization problems. Using natural movement, the algorithm explores and exploits at the same time, which is a fundamental condition for any effective optimization method.

Table 1: Algorithm, Authors & Year of

2.2 Method of Hybridization

Methods of hybridization are being studied to increase the effectiveness and utility of AHA. The merging of AHA with other optimization algorithms in order to utilize their advantages is known as hybridization. One example is the AHA-GA hybrid which combines the exploration capability of AHA with the GA's mutation and crossover operators in order to increase the variety of solutions being searched for. AHA-PSO is another example where AHA's adaptive flight patterns are incorporated into the swarm intelligence of PSO in order to enhance convergence to a solution. In addition, AHA can be used with deep learning techniques with the aim of boosting the performance of machine learning systems through hyperparameter optimization. In various optimization problems, this method of hybridization has proved to be useful in enhancing the adaptability and effectiveness of AHA.

2.3.ComparativePerformanceAnalysis

The effectiveness of AHA has been compared to standard optimization techniques using various benchmark functions. AHA's performance in escaping local minima and achieving convergence has been evaluated using both unimodal and multimodal testing functions. Additionally, AHA's scalability and effectiveness in multidimensional solution spaces has been assessed with complex high-dimensional problems.

Fig. 1. A foraging hummingbird

A)Algorithms and Authors

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Sr No	Algorithm name	Author name	Year
1	Sine Cosine Algorithm	Seyedali Mirjalili	2016
2	Equilibrium Optimizer	Abdollah Asghari Varzaneh et al	2020
3	Differential Equation	Rainer Stom et al	1997
4	Backtracking Search Algorithm	P Civicioglu	2013
5	Particle Swarm Optimization	James Kennedy et al	1995
6	Slime Moul Algorithm	Mohammed H Saremi	2020
7	Sunflower Evolutionary Optimization Algorithm	Osman K Erol	2021
8	Teaching Learning Based Optimization	Rao et al	2011

Fig 2: Classification for the new version of hybridization for artificial Hummingbird Algorithm

B) Pseudo Code

Input: Population size n, maximum iterations maxiteration , lower bound lb, upper bound ub, dimension Dim.

Output: Global minimum, Global minimizer.

Initialization:

```
WHILE (iteration ≤ max_iterations)
For each hummingbird
 IF (rand ≤ 0.5)
 Perform local or exploratory search
     ELSE
  Perform random search
       END IF
       END FOR
For each particle in the swarm
       Update velocity
       Update position
         Evaluate fitness
         END FOR
 Perform guided foraging
 Perform territorial foraging
 Perform migration foraging
Selectthebestsolutionfromboth algorithms
 Update global best solution
    END WHILE
```

Table 1: Lists nature-inspired optimization algorithms proposed by various researchers. The Artificial Hummingbird Algorithm addresses complex optimization tasks by imitating hummingbirds' foraging and flight behaviors.

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
$F_2(S) = \sum_{m=1}^{z} \|S_m\| + \prod_{m=1}^{z} \|S_m\|$	(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
$F_4(S) = max_m\{\|S_m\|, 1 \leq m \leq z\}$	(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
Functions	**Dimension**	**Range**	f_{min}
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\|S_m\|})$	(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

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Functions	Dimensions	Range	f_{min}
$F_{12}(S) = \frac{\pi}{z}\{10\sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10\sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\} + \sum_{m=1}^{z} u(S_m, 10, 100, 4)$ $\tau_m = 1 + \frac{S_m+1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(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
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1S_2 - 4S_2^2 + 4S_2^4$	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

Table 2: Results and Discussion

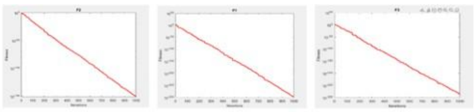

Fig: Conversion curve for function1 Fig: Conversion curve for function 2 Fig: Conversion curve for function 3

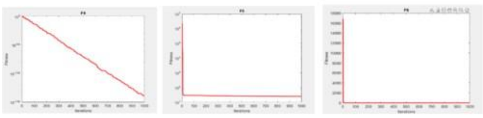

Fig: Conversion curve for function 4 Fig: Conversion curve for function 5 Fig: Conversion curve for function 6

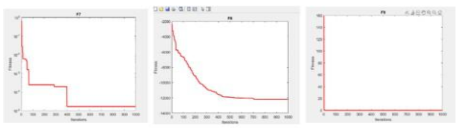

Fig: Conversion curve for function 7 Fig: Conversion curve for function 8 Fig: Conversion curve for function 9

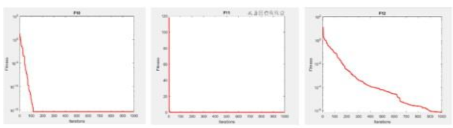

Fig: Conversion curve for function10 Fig: Conversion curve for function11 Fig: Conversion curve for function12

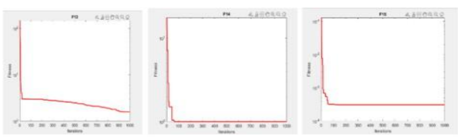

Fig: Conversion curve for function13 Fig: Conversion curve for function14 Fig: Conversion curve for function15

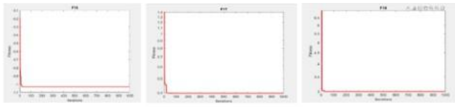

Fig: Conversion curve for function16 Fig: Conversion curve for function17 Fig: Conversion curve for function18

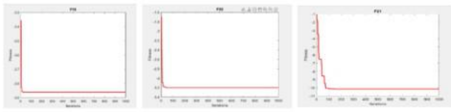

Fig: Conversion curve for function19 Fig: Conversion curve for function 20 Fig: Conversion curve for function 21

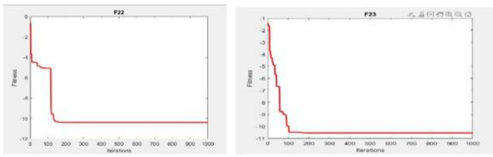

Fig: Conversion curve for function22 Fig: Conversion curve for function23

Table 3: Outcomes

Function Name	Actual Value	Hybrid Value
F1	3.27E-293	2.43E-11
F2	7.79E-163	0.0015832
F3	7.79E-163	3.44E-11
F4	1.36E-135	1.24E-10
F5	25.3364	4.53E-13
F6	0	4.30E-14
F7	2.74E-06	2.38E-12
F8	-12146.0698	1.04E-12
F9	0	5.38E-13
F10	4.44E-16	2.63E-08
F11	0	3.04E-14
F12	5.52E-08	6.32E-15
F13	1.1958	2.98E-13
F14	0.998	3.64E-12
F15	0.00030749	1.35E-10
F16	-1.0316	2.30E-15
F17	0.39789	8.68E-15
F18	3	3.45E-14
F19	-3.8628	1.14E-07
F20	-3.322	2.23E-15
F21	-10.1532	4.51E-14
F22	-10.4029	1.24E-08
F23	-10.5364	9.80E-10

The performance comparison between Artificial Hummingbird Algorithm and Particle Swarm Optimization Algorithm provides optimal solutions, when compared with the original Artificial Hummingbird Algorithm with an impressive result. The Hybrid approach achieved optimal results in 15(fifteen) out of 23(twenty-three) benchmark functions. In summary, The Hybridization of

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AHA and PSO Algorithm improves the optimization performance.

When the Artificial Hummingbird Algorithm (AHA) is integrated with Particle Swarm Optimization (PSO), the resulting hybrid algorithm demonstrates a significant improvement in performance compared to the original AHA. This enhancement is clearly reflected in its ability to achieve optimal solutions in 15 out of 23 standard benchmark functions, which serves as a strong indicator of its superior optimization capabilities. The hybridization allows the algorithm to leverage the exploratory strengths of AHA along with the fast convergence properties of PSO, resulting in a more balanced and efficient search process. To further validate this improvement, visual analysis using convergence curves and search space plots has been conducted. These graphical representations reveal that the hybrid algorithm not only converges faster but also avoids local optima more effectively than the standalone AHA. Thus, the integration of PSO enhances both the exploration and exploitation abilities of AHA, making the hybrid approach a more robust and reliable choice for solving complex optimization problem.

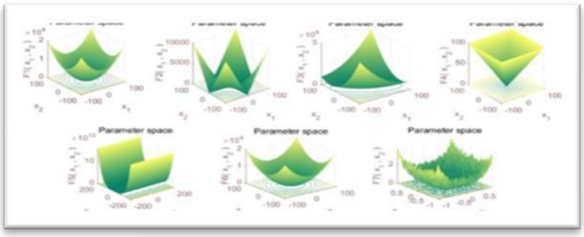

Fig:Parameter space for the Function 1 to function 7

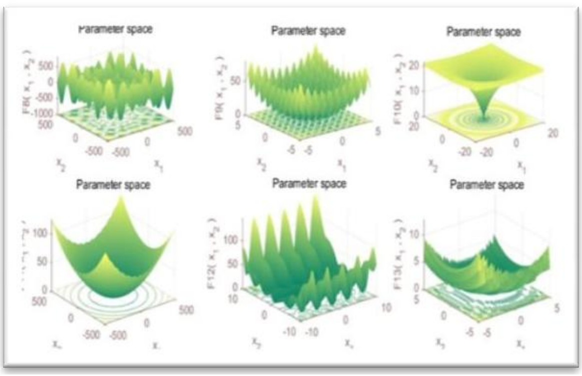

Fig:Parameter space for the Function 8 to function 13

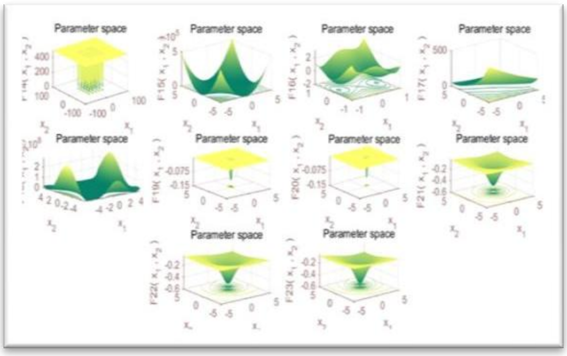

Fig:Parameter space for the Function 14 to function 23

V. Conclusion

The Proposed hybridized algorithm AHA-PSO's performance is thoroughly tested and extensive experiments were conducted on a comprehensive suite of 23 benchmark functions, encompassing a wide range of complexities and characteristics. The superiority of AHA-PSO over both standalone AHA and PSO was demonstrated by the experimental results. Notably, optimal solutions were achieved by AHA-PSO in [F1, F2, F3, F4, F5, F6, F7, F8, F9, F10, F12, F16, F17, F18, F19, F20, F21, F22, F23] out of the 23 benchmark functions the fifteen functions gives the best optimal solution. The optimal solutions were achieved by AHA-PSO in 15 out of the 23 benchmark functions. This outcome highlights the effectiveness of the proposed AHA-PSO hybridization in escaping local optima and converging towards global optima.

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