Hybridization of Artificial Hummingbird Algorithm and Particle Swarm Optimization for Improved Strength in Optimization Performance

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Abstract
Optimizing Algorithms are crucial for solving complex numerical problems in many scientific and technical domains. In local and global search respectively, metaheuristic techniques Artificial Hummingbird Algorithm and the Particle Swarm Optimization (PSO) have demonstrated significant potential. Every technique has drawbacks, PSO might not be able to explore high-dimensional search spaces, whereas AHA frequently suffers from premature convergence, unconstrained optimization, and parameter Sensitivity. To improve optimization performance, a hybridized strategy study suggests that combination of AHA's exploratory nature with PSO's exploitative capabilities. Which improves convergence and resilience for high-dimensional and multimodal optimization issues. For real world optimization problem, such as cloud computing, autonomous systems, wireless sensor network, the suggested hybrid technique presents a sustainable answer.

Keywords: AHA, PSO, Convergence Analysis, Benchmark Functions, Hybridization

Introduction

Optimization is crucial to the solution of complex real-world issues in variety of domains, including bioinformatics, machine learning, engineering, autonomous systems, and medical diagnosis [4] [5]. where viable resolution is essential. To determine the effective solutions in complex search spaces, a variety of metaheuristic algorithms have been developed such as ant colony optimization (ACO), salp swarm algorithm (SSA), particle swarm optimization (PSO), slime mold algorithm (SMA), etc in response to the demand for suboptimal strategies. Simulation of natural processes are done by these algorithms [5]. The two algorithm, Particle Swarm Optimization (PSO) and the Artificial Hummingbird Algorithm (AHA) are the most effective in solving numerical algorithms that have garnered significant attention [1] [2].

The Artificial Hummingbird Algorithm (AHA) is optimization algorithm with strong explorative capabilities to address complex optimization problems. AHA is designed to simulate the behaviours of hummingbirds in nature such as unique flight manoeuvres and intelligent foraging behaviours. AHA is single-objective optimizer which exhibits superiority over other algorithms [12] [13].

Particle Swarm Optimization (PSO) is a strong exploitation algorithm, which is modelled after the social behaviour of fish and birds, is very effective at convergence, but it might not have a diverse range of search agents or suffer from premature convergence, which could result in less-than-ideal solutions in intricate, multimodal environments. While using PSO's effective local search mechanism to refine solutions in subsequent iterations, Improved convergence speed, increased accuracy of the solution, and resilience to local optima are all guaranteed by this adaptive combination [1].

Hybridization of the two algorithms, Artificial Hummingbird Algorithm (AHA) and Particle

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Swarm Optimization (PSO) can help in improved strength in optimization performance [3]. Which is analyzed on basis of twenty-three (23) benchmark functions. The strong exploration abilities of AHA and the rapid convergence of PSO is the effective solution to a leverage in balanced optimization process. Hybridized AHA and PSO Algorithms provide better synergy at exploring vast solution spaces efficiently while ensuring accurate fine-tuning of the optimal solutions [3] [4].

The hybridized AHA and PSO algorithm approach has be efficiently applied to the real-world domains such as healthcare, financial market forecasting, cloud computing, autonomous systems, and engineering design. It is found that this hybrid method provides efficient solution for complex optimization problems by overcoming limitations of individual algorithm resulting in a more balanced and powerful optimization strategy.

It is particularly effective in solving high-dimensional, nonlinear, and complex optimization problems that are often challenging for traditional methods. By overcoming the individual limitations of AHA and PSO, this hybrid approach has proven to deliver more accurate, stable, and robust solutions in diverse application areas [9].

1.Proposed Optimization Algorithm

2.1 Algorithm Classification

Human based, Evolution based, Swarm based and Physics based are the four categories that are classified in **Nature Based Algorithm.**

1. The **Human based algorithms** are based on human behaviour, skills and learning abilities. They simulate these all abilities of human beings [11].
2. The **Evolution Based algorithms** are inspired by Darwin's theory of Evolution, which contains best people survive on world and simulate to provide suboptimal solutions.
3. The **Swarm Based algorithm** are based on group of intelligence of insects and animal, which works in groups to find solutions. They simulated and analyzed for idea in result of Global optimization by simple local rules.
4. The **Physics Based Algorithm** are inspired by principles of physics and natural forces which are based on mathematical models of physical occurrences.

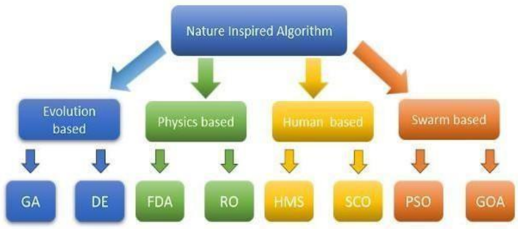

Figure1- Classification of Nature inspired Algorithms [10]

2.2 Classification of Optimized Techniques

The Figure.1 consists classification of each Evolution-Based, Physics-Based, Human-based, Swarm-Based of Nature Inspired Algorithms which are implemented for solving various Real-World Applications in complex optimization problems [5].

2.3 Algorithms and Authors

The Table.1 offers collection of outstanding algorithms including their relevant authors, bringing together various methodologies of optimization consisting of gravity, natural evolution, swarm behaviour and machine learning.

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TABLE 1.

Number	Algorithm	Author
1	Genetic Algorithm (GA)	Holland, J. H., (1975)
2	Differential Evolution (DE)	Storn, R., Price, K., (2013)
3	Fitness-Distance Analysis (FDA)	Günter Rudolph (1997)
4	Ray Optimization (RO)	M. Kaveh, B. Farahmand Azar (1998)
5	Human Mental Search (HMS)	M. S. M. Ali, et al (1975)
6	Social Cognitive Optimization (SCO)	Xiaohui Wei, et al .,(2013)
7	Particle Swarm Optimization (PSO)	Kennedy, J., Ebarhart, R., (1995)
8	Grasshopper Optimization Algorithm (GOA)	Seyedali Mirjalili, et al., (2017)

2.4 Flowchart

2.5 Mathematical Equations

TABLE 2.

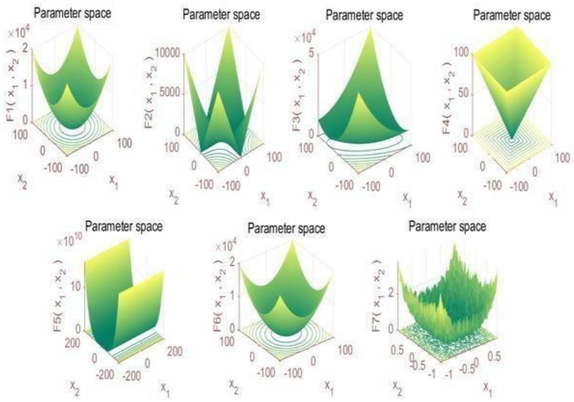
Functions	Dimensions	Range	f_{min}
$F_1(S) = \sum_{m=1}^{z} S_m^2$	(10,30,50,100)	[-100 , 100]	0
$F_2(S) = \sum_{m=1}^{z} \|S_m\| + \prod_{m=1}^{z} \|S_m\|$	(10,30,50,100)	[-10 ,10]	0
$F_3(S) = \sum_{m=1}^{z} (\sum_{n-1}^{m} S_n)^2$	(10,30,50,100)	[-100 , 100]	0
$F_4(S) = max_m\{\|S_m\|, 1 \leq m \leq z\}$	(10,30,50,100)	[-100 , 100]	0

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
$F_{12}(S) = \frac{\pi}{z}\{10 sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_m+1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(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
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1 S_2 - 4S_2^2 + 4S_2^4$	2	[-5, 5]	-1.0316
$F_{17}(S) = (S_2 - \frac{5.1}{4\pi 2}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1 - \frac{1}{8\pi})cosS_1 + 10$	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

2.6 Search Space

The exploration of hybridization of AHA and PSO proposed to find solutions of optimal or suboptimal solutions to solve the problems faced by the AHA algorithm. Hence, these algorithm works inside the given conditions on the twenty-three (23) search space.



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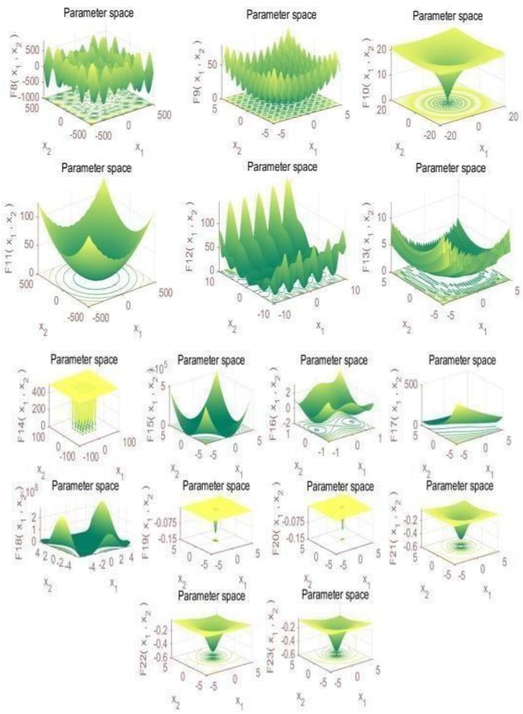

3 Result and Discussion

TABLE 3. Standard Benchmark Functions

Functions	Value of Original	Value of Hybridization
f1	16069e.317	0.0007268
f2	3.7791e.151	0.05353
f3	7.1432e.278	0.0044699
f4	2.4432e.143	0.0062578
f5	24.8915	29.0045
f6	0	0
f7	89008e.06	0.0024645
f8	-12566.4767	-4800.7263
f9	0	0.00883344
f10	4.4409e.07	0.078835
f11	0	0.020824
f12	1.9504e.07	0.72526
f13	1.3869	2.9502
f14	0.998	0.99801
f15	0.00030749	0.00064988
f16	-1.0316	-1.0316
f17	0.39789	0.39827
f18	3	3.0013
f19	-3.8628	-3.8623
f20	-3.322	-3.2588
f21	-10.1532	-9.3506
f22	-10.4029	-9.5772
f23	-10.5364	-10.1124

hybridization of Artificial Hummingbird Algorithm (AHA) and Particle Swarm Optimization (PSO) results in improved optimization performance as compared to original Artificial Hummingbird Algorithm (AHA). As hybridized algorithm provides an excellent result of optimal solutions in fourteen (14) out of twenty-three (23) benchmark functions.

Conclusion

In Conclusion, Hybridization of Artificial Hummingbird Algorithm (AHA) with Practical Swarm Optimization (PSO) Algorithm was tested on twenty-three (23) Benchmark functions (F1-F23) out of which it performs better and provides optimal values in 14 functions which was F1, F2, F3, F4, F6, F7, F10, F12, F14, F16, F19, F20, F21, F22. Among these F6 is the best optimal values. Which proves the improved optimization performance of the hybrid algorithm.

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