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A Novel Adaptive Whale Optimization Algorithm for Global Optimization

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Abstract

Background/Objectives: In the meta-heuristic algorithms, randomization plays a very crucial role in both exploration and exploitation. So meta-heuristic algorithms are proposed to avoid these problems. **Methods/Statistical Analysis**: A novel bio-inspired optimization algorithm based on the special bubble-net hunting strategy used by humpback whales called the Whale Optimization Algorithm (WOA). In contrast to meta-heuristic, main feature is randomization having a relevant role in both exploration and exploitation in optimization problem. A novel randomization technique termed adaptive technique is integrated with WOA and exercised on ten unconstraint test benchmark function. **Findings:** WOA algorithm has quality feature that it uses logarithmic spiral function so it covers a broader area in exploration phase then addition with powerful randomization adaptive technique potent the adaptive whale optimization Algorithm (AWOA) to attain global optimal solution and faster convergence with less parameter dependency. **Application/Improvements:** Adaptive WOA (AWOA) solutions are evaluated and results shows its competitively better performance over standard WOA optimization algorithm.

Keywords: Adaptive Technique, Exploitation, Exploration, Hunting, Optimization, Whale Optimization Algorithm

1. Introduction

In the meta-heuristic algorithms, randomization plays a very crucial role in both exploration and exploitation. More strengthen randomization techniques are Markov chains, Levy flights and Gaussian or normal distribution and **newest technique** is adaptive technique. So meta-heuristic algorithms on integrated with adaptive technique results in less computational time to reach optimum solution, local minima avoidance and faster convergence.

Population based WOA[1] is a meta-heuristic optimization algorithm has an ability to avoid local optima and get global optimal solution that make it appropriate for practical applications without structural modifications in algorithm for solving different constrained or unconstraint optimization problems. WOA integrated with adaptive technique reduces the computational times for highly complex problems.

Contemporary works with adaptive technique are: Adaptive Cuckoo Search Algorithm (ACSA)[2,3], QGA[4], Acoustic Partial discharge (PD)[5,6], HGAPSO[7], PSACO[8], HSABA[9] PBILKH[10], KH-QPSO[11], IFA-HS[12], HS/FA[13], CKH[14] HS/BA[15] HPSACO[16] CSKH[17], HS-CSS[18], PSOHS[19], DEKH[20], HS/CS[21], HSBBO[22], CSS-PSO[23] etc.

The structure of the paper can be given as follows: - Section I consists of Introduction; Section II includes

description of main algorithms; section III consists of competitive results analysis of unconstraint test benchmark problem; finally, acknowledgement and conclusion based on results is drawn.

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2. Whale Optimization Algorithm

In the meta-heuristic algorithm, a newly purposed optimization algorithm called Whale optimization algorithm (WOA), which inspired from the bubble-net hunting strategy. Algorithm describes the special hunting behavior of humpback whales, the whales follows the typical bubbles causes the creation of circular or '9-shaped path' while

encircling prey during hunting. Simply bubble-net feeding/hunting behavior could understand such that humpback whale went down in water approximate 10-15 meter and then after the start to produce bubbles in a spiral shape

encircles prey and then follows the bubbles and moves upward the surface. Mathematic model for Whale Optimization algorithm (WOA) is given as follows:

a. Encircling Prey Equation

Humpback whale encircles the prey (small fishes) then updates its position towards the optimum solution over the course of increasing number of iteration from start to a maximum number of iteration.

$$\vec{D} = \left|C.\vec{X}*(t) - X(t)\right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}*(t) - \vec{A}.\vec{D} \tag{2}$$

Where: $\vec{A}$, $\vec{D}$ are coefficient vectors, t is a current iteration, $\vec{X}*(t)$ is position vector of the optimum solution so far and $X(t)$ is position vector.

Coefficient vectors $\vec{A}$, $\vec{D}$ are calculated as follows:

$$\vec{A} = 2\vec{a}*r - \vec{a} \tag{3}$$

$$\vec{C} = 2*r \tag{4}$$

Where: $\vec{a}$ is a variable linearly decrease from 2 to 0 over the course of iteration and r is a random number [0, 1].

b. Bubble-net Attacking Method

In order to mathematical equation for bubble-net behavior of humpback whales, two methods are modeled as:

(a) Shrinking Encircling Mechanism

This technique is employed by decreasing linearly the value of $\vec{a}$ from 2 to 0. Random value for avector $\vec{A}$ in range between [-1, 1].

(b) Spiral Updating Position

Mathematical spiral equation for position update between humpback whale and prey that was helix-shaped movement given as follows:

$$\vec{X}(t+1) = \vec{D}'* e^{bt} * \cos(2\pi l) \quad \vec{X}*(t) \tag{5}$$

Where: l is a random number [-1, 1], b is constant defines thelogarithmic shape, $\vec{D}' = \left|\vec{X}*(t) - X(t)\right|$ expresses the distance between i^{th} whale to the prey mean the best solution so far.

Note: We assume that there is 50-50% probability that whale either follow the shrinking encircling or logarithmic path during optimization. Mathematically we modeled as follows:

$$\vec{X}(t+1) = \begin{cases} \vec{X}*(t) - \vec{A}.\vec{D} & if \quad p < 0.5 \\ \vec{D}'.e^{bl}.\cos(2\pi l) + \vec{X}*(t) & if \quad p \geq 0.5 \end{cases} \tag{6}$$

Where: p expresses random number between [0, 1].

(c) Search for Prey

The vector $\vec{A}$ can be used for exploration to search for prey; vector $\vec{A}$ also takes the values greater than one or less than -1. Exploration follows two conditions

$$\vec{D} = \left|\vec{C}.\vec{X_{rand}} - \vec{X}\right| \tag{7}$$

$$\vec{X}(t+1) = \vec{X_{rand}} - \vec{A}.\vec{D} \tag{8}$$

Finally follows these conditions:

- $|\vec{A}| > 1$ enforces exploration to WOA algorithm to find out global optimum avoids local optima
- $|\vec{A}| < 1$ For updating the position of current search agent/best solution is selected.

3. Adaptive Whale Optimization Algorithm (AWOA)

The Adaptive technique includes best features like it consists of less parameter dependency, not required to

define initial parameter and step size or position towards optimum solution is adaptively changes according to its

functional fitness value over the course of iteration. So mete-heuristic algorithms on integrated with adaptive

technique results in less computational time to reach optimum solution, local minima avoidance and faster

convergence.

Table 1. Benchmark Test Function

No.	Name	Function	Dim	Range
F1	Sphere	$f(x)=\sum_{i=1}^{n}x_i^2 * R(x)$	10	[-100, 100]
F2	Schwefel 2.22	$f(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert * R(x)$	10	[-10, 10]
F3	Schwefel 1.2	$f(x)=\sum_{i=1}^{n}\left(\sum_{j=1}^{i}x_j\right)^2 * R(x)$	100	[-100, 100]
F4	Schwefel 2.21	$f(x)=\max_i\{\lvert x_i\rvert, 1\le i\le n\}$	10	[-100, 100]
F5	Rosenbrock's Function	$f(x)=\sum_{i=1}^{n-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right] * R(x)$	100	[-30, 30]
F6	Step Function	$f(x)=\sum_{i=1}^{n}\left([x_i+0.5]\right)^2 * R(x)$	100	[-100, 100]
F7	Quartic Function	$f(x)=\sum_{i=1}^{n}ix_i^4+random[0,1) * R(x)$	100	[-1.28, 1.28]
F8	Schwefel 2.26	$F(x)=\sum_{i=1}^{n}-x_i sin\left(\sqrt{\lvert x_i\rvert}\right) * R(x)$	100	[-500, 500]
F9	Penalty 1	$F(x)=\frac{\pi}{n}\begin{Bmatrix}10sin(\pi y_1)+\sum_{i=1}^{n-1}(y_i-1)^2\\ \left[1+10sin^2(\pi y_{i+1})\right]+(y_n-1)^2\end{Bmatrix}$ $y_i=1+\frac{x_i+1}{4},$ $u(x_i,a,k,m)=\begin{cases}k(x_i-a)^m & x_i>a\\ -0< \; < & a \; x_i \; a\\ k(-x_i-a)^m & x_i<-a\end{cases}$	10	[-50, 50]
F10	Penalty 2	$F(x)=0.1\begin{Bmatrix}sin^2(3\pi x_1)+\sum_{i=1}^{n}(x_i-1)^2\\ \left[1+sin^2(3\pi x_i+1)\right]\\ +(x_n-1)^2\left[1+sin^2(2\pi x_n)\right]\end{Bmatrix}$ $+\sum_{i=1}^{n}u(x_i,5,100,4) * R(x)$	10	[-50, 50]

Table 2. Internal Parameters

Parameter Name	Search Agents no.	Max. Iteration no.	No. of Evolution
F1-F10	30	500	5-10

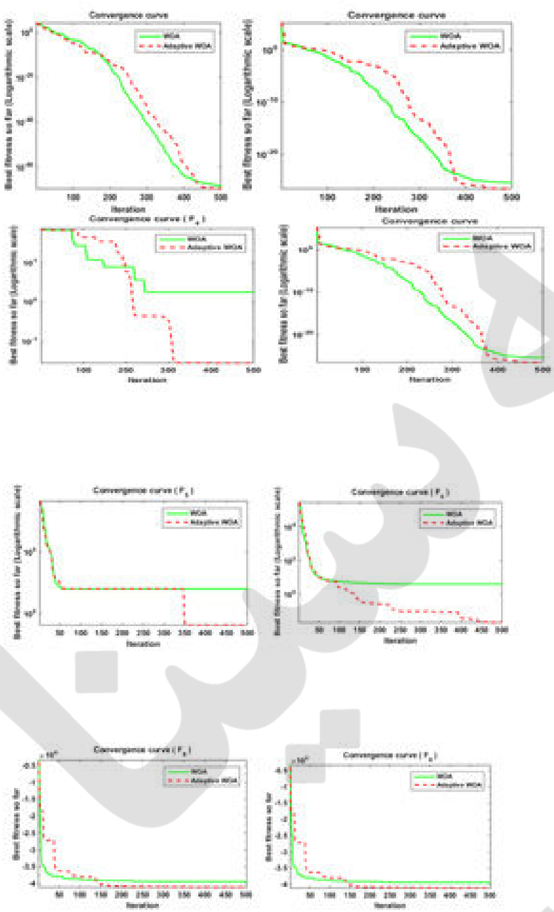

Figure 1. Convergence curve of test function.

$$X_i^{t+1} = X_i^t + randn * \left(\frac{1}{t}\right)^{\left|((bestf(t) - fi(t))/(bestf(t) - worstf(t)))\right|} \quad (9)$$

Where X_i^{t+1} new solution of *i-th* dimension in *t-th* iteration $f(t)$ is the fitness value.

4. Simulation Results for Unconstraint Test Benchmark Function

Unconstraint Test Benchmark Functions (Sphere, Schwefel 2.22, Schwefel 1.2, Schwefel 2.21, Rosenbrock's function, Step Function, Quartic Function, Schwefel 2.26, Penalty 1,2 etc.) are given in Table I and internal parameters are given in Table II. Results are given in Table III. Here we consider high dimension to test its effectiveness of new AWOA strategy. Internal parameter also plays vital role so these are clearly expressed in Table I. Convergence curve of test function is shown in Figure I that's proof that AWOA algorithm has very good results compare to standard recently Proposed Whale Optimization Algorithm (WOA).

5. Conclusion

Whale optimization Algorithm has an ability to find out optimum solution with constrained handling which includes both equality and inequality constraints. While obtaining optimum solution constraint limits should not be violated. Adaptive technique causes faster convergence,

Table 3. Statical Results

Fun.	Whale Optimization Algorithm (WOA)			Adaptive WOA (AWOA)		
	Ave	**Best**	**S.D.**	**Ave**	**Best**	**S.D.**
F1	8.0771e-69	1.9381e-69	8.6819e-69	6.7908e-57	**1.7272e-70**	9.6036e-57
F2	6.7699e-24	3.7467e-26	9.5211e-24	1.2349e-24	**2.5846e-27**	1.7427e-24
F3	1411753.69	1180140.733	327550.185	1251270.94	**1065090.031**	263299.6148
F4	8.2428	1.7214	9.2226	0.21458	**0.027739**	0.26423
F5	98.2835	98.2749	0.012064	0.14324	**0.11416**	0.041135
F6	4.659	3.9536	0.99749	0.032477	**0.021538**	0.015471

F7	0.00080305	0.00067362	0.00018304	0.002901	**0.00061163**	0.0032378
F8	-35649.227	-39442.0078	5363.8013	-34729.685	**-41077.2577**	8976.8229
F9	0.013828	0.0090427	0.0067677	0.002071	**0.00062873**	0.0020396
F10	0.091796	0.039021	0.074636	0.030366	**0.0037635**	0.037622

randomness, and stochastic behavior for improving solutions. Adaptive technique also used for random walk in search space when no neighboring solution exits to converse towards optimal solution. The AWOA result of various unconstrained problems proves that it is also an effective method in solving challenging problems within unknown search space.

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