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Adjustive Reciprocal Whale Optimization Algorithm for Wrapper Attribute Selection and Classification

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Abstract—One of the most difficult challenges in machine learning is the data attribute selection process. The main disadvantages of the classical optimization algorithms based attribute selection are local optima stagnation and slow convergence speed. This makes bio-inspired optimization algorithm a reliable alternative to alleviate these drawbacks. Whale optimization algorithm (WOA) is a recent bio-inspired algorithm, which is competitive to other swarm based algorithms. In this paper, a modified WOA algorithm is proposed to enhance the basic WOA performance. Furthermore, a wrapper attribute selection algorithm is proposed by integrating information gain as a preprocessing initialization phase. Experimental results based on twenty mathematical optimization functions demonstrate the stability and effectiveness of the modified WOA when compared to the basic WOA and the other three well-known algorithms. In addition, experimental results on nine UCI datasets show the ability of the novel wrapper attribute selection algorithm in selecting the most informative attributes for classification tasks.

Index Terms—Bio-inspired algorithm, Whale Optimization, Reciprocal spiral, Information Gain, Attribute selection, Classification.

I. Introduction

Dimensionality reduction is a critical procedure in pattern recognition and data mining, which contributes towards boosting the performance of a classification model. For high-dimensional datasets, large number of attributes may contain a lot of redundancy [1]. Therefore, attribute selection plays a pivotal role to increase the accuracy of the classification models as well as the learning speed. Attribute selection methods fall under two categories based on the evaluation criteria: Filter approach and wrapper approach. The filter approaches evaluate the new set of attributes depending on the statistical characteristics of the data without involving any machine algorithm. While, wrapper approaches use the classification performance of a predetermined machine algorithm as the evaluation criterion to select the new attributes subset [2, 3].

Attributes selection is a combinatorial problem with a large search space; in which, the search space size grows exponentially along with the total number of attributes. Thus, an exhaustive search for the optimal attributes subset in a high dimensional space is impractical. This motivate for employing bio-inspired algorithms which show higher computational efficiency in avoiding local minima [4-7].

Bio-inspired optimization algorithms draw their inspiration from swarm intelligence, where they imitate the social behavior of natural creatures such as ants [8], fishes [9], bats [10], bees [11] and particle swarms [12]. Swarm-based algorithms incorporate randomness to move from a local search to a global search; as a result, they are more suitable for global optimization and can be applied to various applications including attribute selection problems [13, 14].

Whale optimization algorithm (WOA) is a new bio-inspired optimization algorithm proposed by Mirjalili and Lewis [13]. WOA mimics the hunting behavior of the humpback whales. A binary version of the Whale optimization is proposed for selecting the optimal attribute subset [16]. However, as the expansion of the search space dimension; WOA is easily trapped in the local optimum and provide poor convergence. Consequently, a number of variants are proposed to improve the performance of the basic WOA.

Hu et al. proposed different inertia weights with whale optimization algorithm (IWOA). Results show that the IWOAs are very competitive for prediction compared with basic WOA and PSO [17].

Ling et al. developed an enhanced version of WOA using Lèvy flight trajectory, and called it Levy flight trajectory-based whale optimization algorithm (LWOA). The Lèvy flight trajectory increases the diversity of the population and enhances its capability of avoiding the local optima [18].

Mafarja and Mirjalili proposed two hybridized attribute selection models based on WOA. In the first model, simulated annealing (SA) algorithm is embedded to WOA algorithm, while in the second model; it is used to improve the best solution found by the WOA algorithm. Experimental results confirm the efficiency of the proposed SA-WOA models for improving the classification accuracy [19].

Following these streams, this paper presents two major contributions:

1. Proposing Reciprocal adapted WOA (RaWOA), where reciprocal spiral is adopted to simulate the spiral updating position of the WOA bubble-net behavior.
2. Introducing information gain RaWOA (IRaWOA) for solving attributes selection problems. For which, Information gain (IG) is obtained as a pre-processing phase to guarantee a large initialization of the RaWOA algorithm.

The proposed RaWOA is tested under twenty benchmark functions, while IRaWOA is tested on nine UCI datasets. Experimental results demonstrate the efficiency and superiors of the proposed algorithms in most cases.

The rest of this paper is organized as follows: Section II briefly overviews the whale optimization algorithm while Section III presents the details of the proposed RaWOA algorithm. Section IV, discusses the proposed IRaWOA based attribute selection method. Experimentation design, results and comparative analysis occupy the remainder of the paper in Section V. Finally, Section VI summarizes the main findings of this study.

II. Whale Optimization Algorithm

Whale optimization algorithm (WOA) is a recent bio-inspired optimization algorithm that proposed by [13]. It simulates the Humpback whales social hunting behavior in finding and attacking preys. WOA simulates the double-loops and upward-spirals bubble-net hunting strategy. For which, whales dive down creating bubbles in a spiral shape around the prey and then swim up toward the surface; as shown in figure 1.

To find the global optimum of a given optimization problem using WOA; the search process starts with assuming a set of candidate solutions. Then, the search agents update their positions towards the best search agent until the termination criteria is reached.

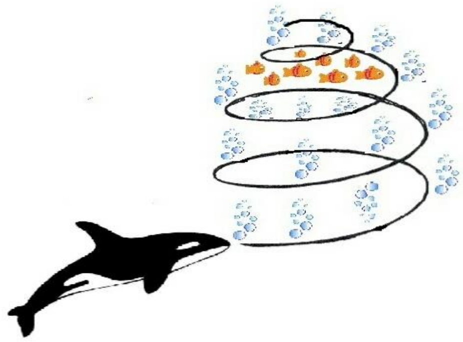


Fig.1. Humpback Whales bubble-net hunting strategy

The mathematical model of the humpback whales behavior is given by equation 1. For which, a probability of 0.5 is assumed to choose between updating either the shrinking encircling or the spiral mechanism during the optimization.

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

p is a random number ϵ [0, 1], t is the current iteration, X' is the best solution position vector obtained so far, X is the position vector, b is a constant defining the spiral shape and l is a random number ϵ [−1, 1] and $\vec{D}$ is given by:

$$\vec{D} = |\vec{C}.\vec{X}'(t) - \vec{X}(t)| \quad (2)$$

While, $\vec{A}$ and $\vec{C}$ are coefficient vectors, calculated by:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad (3)$$

$$\vec{C} = 2.\vec{r} \quad (4)$$

Where $\vec{a}$ linearly decreased from 2 to 0 over the course of iterations and $\vec{r}$ is a random vector ϵ [0, 1].

The distance of the I th whale to the best solution obtained so far is indicated by:

$$\vec{D}' = |\vec{X}'(t) - \vec{X}(t)| \quad (5)$$

In order to have a global optimizer, vector $\vec{A}$ used random values within $1 < \vec{A} < -1$; whereby the agent position is updated according to a randomly chosen agent $\vec{X}_{rand}(t)$:

$$\vec{D}' = |C.\vec{X}_{rand}(t) - \vec{X}(t)| \quad (6)$$

$$\vec{X}(t+1) = \vec{X}_{rand}(t) - \vec{A}.\ \vec{D} \quad (7)$$

III. PROPOSED RECIPROCAL WHALE OPTIMIZATION ALGORITHM

In WOA algorithm, the desirable way to simulate the bubble-net behavior of humpback whales can be divided into two approaches: shrinking encircling mechanism and spiral updating position. For the WOA algorithm a spiral movement of whale around the prey is created to mimic the helix-shaped movement based on equation 1 (b). For which, a logarithmic spiral is chosen for the basic WOA algorithm.

The proposed reciprocal adapted WOA algorithm (RaWOA) aims to employ a reciprocal (hyperbolic) spiral to simulate the spiral updating position of the bubble-net behavior over the course of iterations. The reciprocal spiral using the polar equation of the form $r = a/\theta$, where, r and θ are the radius and azimuthal angle in a polar coordinate system, respectively, and a is real number constant. As θ increases, the spiral winds around the origin and moves closer to it. Figure 2 shows the reciprocal spiral and its hyperbolic counterpart. Thus, for RaWOA, the reciprocal spiral updating position of the whale is given by the following equation:

$$\vec{X}(t+1) = \vec{D}'.\frac{\cos(2\pi l)}{l} + \vec{X}'(t) \quad (8)$$

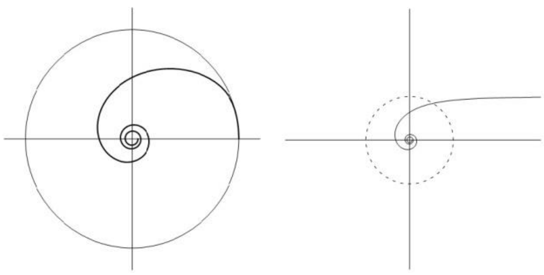


Fig.2. The reciprocal spiral and its hyperbolic counterpart

IV. RaWOA FOR ATTRIBUTE SELECTION PROBLEM

In order to solve attribute selection problems, a novel Information gain RaWOA algorithm (IRaWOA) is proposed. The expected value of the information gain (IG) is the mutual information I(C|a) of C and a. As a result, it is the reduction in the entropy of class C achieved by learning the state of attribute a.

At IRaWOA attribute selection algorithm, the whale positions is represented by a binary vector; either "1" indicating the corresponding attribute is selected or "0" for non selected attributes. IRaWOA adapted IG for performing the population initialization phase; for which, any attributes with a corresponding entropy is represented by "1"; otherwise its value is set to "0". The IG initialization phase of the IRaWOA guarantee a large initialization; which leads to improve the local searching capability as the agents positions are commonly near to the optimal solution.

Attribute selection has two main objectives; minimizing the number of attributes while maximizing the classification accuracy. Therefore, IRaWOA is used to adaptively search for the best attributes combination, which considers these two objectives. The fitness function adopted to evaluate each individual whale positions is given by:

$$\text{Fitness} = \propto E_R + (1-\propto)\frac{|S^*|}{|S|} \quad (9)$$

where E_R is the classification error rate of the selected attributes, S^* is the number of selected attributes and S is the total number of attributes. α and $(1-\alpha)$ represent the relative importance of the classification accuracy and the number of selected attributes, $\alpha \in (0.5, 1]$.

The pseudo code of IRaWOA is given in Algorithm 1:

Algorithm 1. Pseudo code of IRaWOA Algorithm

Input:
Number of whales n
Number of iterations Max_Iter
Output:
Optimal whale binary position X^*

```
Calculate the entropy of each attribute f∈ dataset.
Initialize the n whales population positions ∈ entropy( f) > 1.
Initialize a, A and C.
t=1
while t ≤ Max_Iter do
    Calculate the fitness of every search agent.
    X*= the best search agent.
    for each search agent do
        Update a,A, C and l
        Generate randomly p ∈ [0,1]
        if p < 0.5 then
            if |A| < 1 then
                update X_{t+1} by equation 1(a)
            else if |A| ≥ 1 then
                choose a random search agent X_rand
                update X_{t+1} by equation 7
            end if
        else if p > 0.5 then
            Update position X_{t+1} by equation 8
        end if
        Calculate the fitness of every search agent
        Update X* if there is a better solution
    end for
    t=t+1
end while
return X*
```

V. EXPERIMENTS AND DISCUSSION

The efficiency of the proposed RaWO and *IRaWOA* algorithm in this study was tested using twenty mathematical functions and nine UCI datasets as given bellow.

A. *Results and Analysis of RaWOA*

To evaluate the efficiency of the proposed RaWO algorithm; 20 mathematical functions were used. The optimization functions are divided into three categories: unimodal, multimodal and fixed-dimension multimodal; as shown in tables 1-3. Figure 3 shows the graphical presentation of the cost function for F1,F2, F10 and F20 test problem.

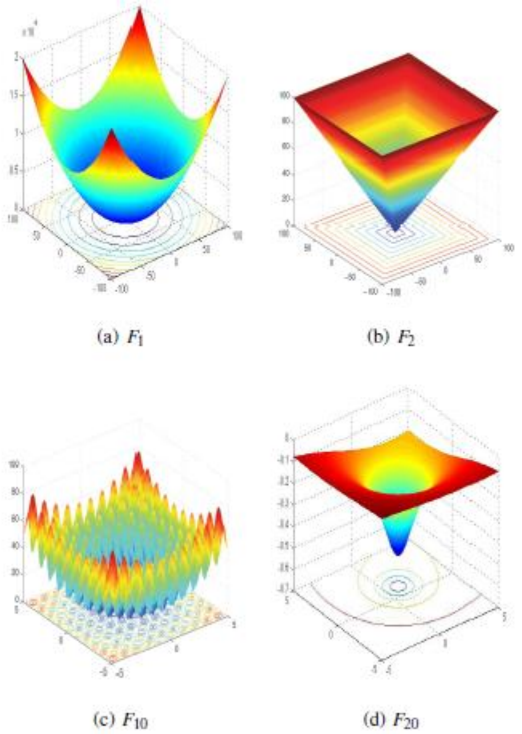


Fig.3. Graphical representations of the benchmark functions

The proposed RaWOA algorithm was run 30 independent times for each optimization functions; and the statistical results; average cost function (av) and standard deviation (std) are recorded. Whereby, RaWOA is compared against the basic WOA, and a swarm based algorithms: Particle Swarm Optimization (PSO) [12], Physics-based algorithm: Gravitational Search Algorithm (GSA) [20] and Evolutionary algorithm: Differential Evolution (DE) [21]; as reported in Table 4. Most of the results of the comparative algorithms are taken from [22].

To evaluate the exploitation capability of RaWOA algorithms, unimodal functions are used as they have only one global optimum. According to Table 4, RaWOA delivers better results than the basic WOA. In particular, RaWOA shows performance enhancing than WOA for functions F1 − F3 and F5 − F7. The large difference in performance of RaWOA versus WOA is directly related to applying the reciprocal spiral to simulate the spiral updating position. Moreover, RaWOA is the most efficient optimizer for functions F1, F2 and F7 and the second best for functions F3 and F5 compared to PSO, GSA and DE. As a result, the RaWOA algorithm can provide a very good exploitation behavior.

On the other hand, multimodal functions allow evaluating the exploration capability of a given optimizer as they possess many local minima. Also, fixed-dimension multi-modal functions present a good optimization challenge as they provide a different search space compared to multimodal functions. Table 4, results indicate that RaWOA shows better performance than the basic WOA in case of functions F8, F10 − F15 and F17 − F20; and produces a similar results to WOA for F9 and F16. While given the second best performance for function F12 and F14. Hence, RaWOA reveals its optimization capability towards the global optimum.

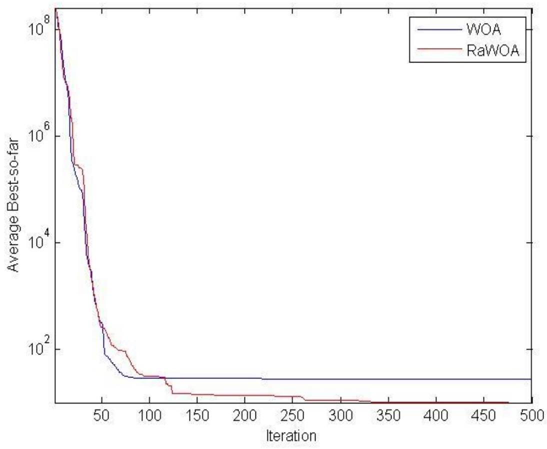
Figure 4 provides the convergence characteristics of the RaWOA and WOA best fitness values versus the iterations over the different runs. As illustrated, the RaWOA algorithm shows a quick convergence from the initial steps of iterations. Consequently, the RaWOA can avoid being trapped into local optimal solutions.

Table 1. Unimodal benchmark

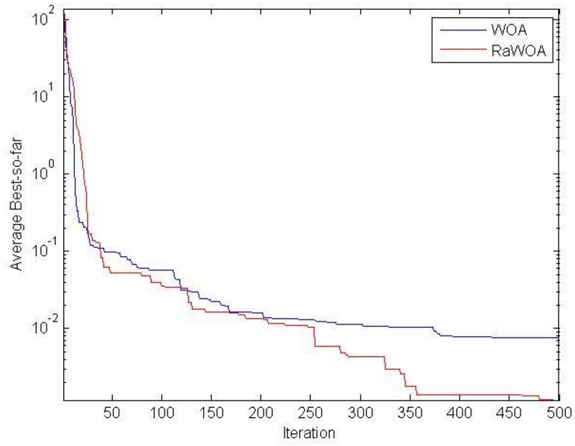
Function	Dim	Range	F_{min}
$F_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-100,100]	0
$F_2(x) = \sum_{i=1}^{n} \lvert x_i\rvert + \prod_{i=1}^{n} \lvert x_i\rvert$	30	[-10,10]	0
$F_3(x) = \sum_{i=1}^{n} (\sum_{j-1}^{i} x_j)$	30	[-100,100]	0
$F_4(x) = max_i\{\lvert x_i\rvert, 1 \le i \le n\}$	30	[-100,100]	0
$F_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30,30]	0
$F_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	[-100,100]	0
$F_7(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1)$	30	[-1.28,1.28]	0

B. *Results and Analysis of IRaWOA*

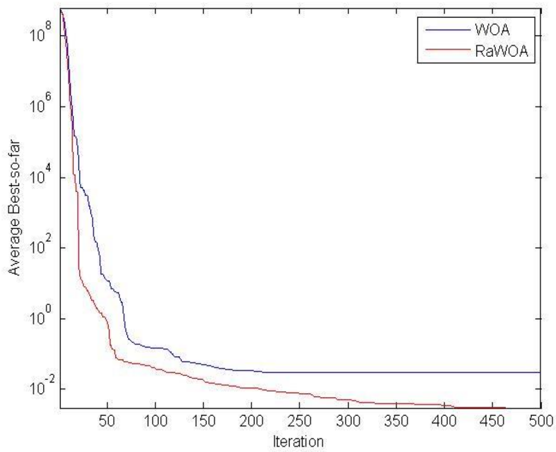
Several experiments on nine datasets from the UCI machine learning repository [23] are conducted to evaluate the performance of the proposed IRaWO attribute selection algorithm. The nine datasets were chosen to have various numbers of attributes, classes and instances; as shown in Table 5.



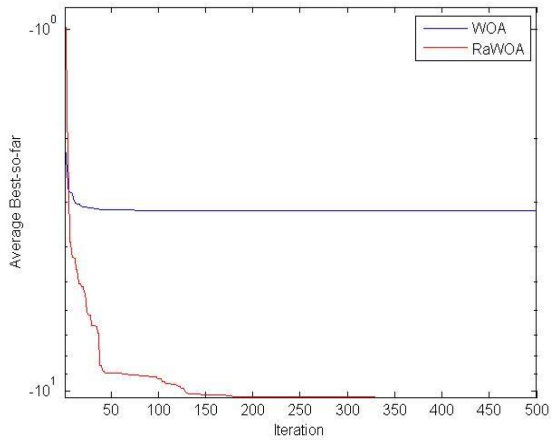
F5



F7



F12



F20

Fig.4. Best fitness convergence curves of WOA and RaWOA

For each dataset, the instances are randomly divided into a cross validation manner to three sets: training, validation and test sets. The partitioning of the instances are repeated for 30 independent runs, and for each run the average accuracy (Av_Acc), best accuracy (Best_Acc) and the standard deviation (Std); are recorded on the test sets.

Table 6, illustrates the overall performance of the proposed IRaWOA attribute selection algorithm, to assess the effect of applying IG preprocessing analog with the RaWOA algorithm. In addition, IRaWOA is compared with three state of the art attribute selection methods; genetic algorithm (GA), particle swarm optimization (PSO) and ant colony optimization (ACO).

From Table 6, it is clear that the IRaWOA outperforms these three algorithms in term of the average accuracy on all datasets, except for the Diabetic dataset; and in term of best accuracy except for the Segment dataset. Meanwhile, in all datasets, ICaXWOA shows a better performance in term of standard deviation values, which indicates the stability of the proposed IRaWOA against other attribute selection algorithm. To examine the attribute selection capability of the IRaWOA, it is tested using different well known classifiers SVM, J48 and NB; as shown in tables 7-9. IRaWOA shows a significant superiority for reducing the number of attribute, hence increasing the classification accuracy compared to the full dataset and WOA.

Table 2. Multimodal benchmark.

Function	Dim	Range	F_{min}
$F_8(x)=\sum_{i=1}^{n}-x_i\sin(\sqrt{\lvert x_i\rvert})$	30	[-500,500]	-418.98295
$F_9(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	30	[-5.12,5.12]	0
$F_{10}(x)=-20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}-\exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i))+20+e$	30	[-32,32]	0
$F_{11}(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	30	[-600,600]	0
$F_{12}(x)=\frac{\pi}{n}10\sin(\pi y_1)+\sum_{i=1}^{n-1}(y_i-1)^2[1+10\sin^2(\pi y_{i+1})]+(y_n-1)^2+\sum_{i=1}^{n}u(x_i,10,100,4)$ $y_i=1+\frac{x_i+1}{4}u(x_i,a,k,m)=\begin{cases}k(x_i-a)^m x_i>a\\ 0-a<x_i<a\\ k(-x_i-a)^m x_i<-a\end{cases}$	30	[-50,50]	0
$F_{13}(x)=0.1\{\sin^2(3\pi x_1)+\sum_{i=1}^{n}(x_i-1)^2[1+\sin^2(3\pi x_i+1)]+(x_n-1)^2[1+\sin^2(2\pi)x_n]\}+\sum_{i=1}^{n}u(x_i,5,100,4)$	30	[-50,50]	0

Table 3. Fixed-dimension multimodal benchmark

Function	Dim	Range	F_{min}
$F_{14}(x)=\sum 1\,1_{i=1}[a_i-\frac{x_1(b_i^2+b_iX_2)}{b_i^2+b_iX_3+x_4}]^2$	4	[-5,5]	0.00030
$F_{15}(x)=(x_2-\frac{5.1}{4\pi^2}x_1^2+\frac{5}{\pi}x_1-6)^2+10(1-\frac{1}{8\pi})\cos x_1+10$	2	[-5,5]	0.398
$F_{16}(x)=[1+(x_1+x_2+1)^2(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)]\times[30+(2x_1-3x_2)^2\times(18-32x_1=12x_1^2+48x_2-36x_1x_2+27x_2^2)]$	2	[-2,2]	3
$F_{17}(x)=\sum_{i=1}^{4}c_i\exp(-\sum_{j=1}^{3}a_{ij}(x_j-p_{ij})^2)$	3	[1,3]	-3.86
$F_{18}(x)=\sum_{i=1}^{4}c_i\exp(-\sum_{j=1}^{6}a_{ij}(x_j-p_{ij})^2)$	6	[0,1]	-3.32
$F_{19}(x)=\sum_{i=1}^{7}[(X-a_i)(X-a_i)^T+c_i]^{-1}$	4	[0,10]	-10.4028
$F_{20}(x)=\sum 1\,0_{i=1}[(X-a_i)(X-a_i)^T+c_i]^{-1}$	4	[0,10]	–10.5363

Table 4. Optimization results obtained for different benchmark functions.

Function	RaWOA		WOA		PSO		GSA		DE	
	av	std	av	std	av	std	av	std	av	std
F1	**2.6562e-56**	**9.84e-51**	1.41e-30	4.91e-30	0.000136	0.000202	2.53e-16	9.67e-17	8.2e-14	5.9e-14
F2	**5.755e-32**	**9.95e-22**	1.06e-21	2.39e-21	0.042144	0.045421	0.055655	0.194074	1.5e-09	9.9e-10
F3	2.748e-9	1.8689	5.3901e-07	2.9310e-06	70.12562	22.11924	896.5347	318.9559	**6.8e-11**	**7.4e-11**
F4	0.5389	0.2921	0.072581	0.39747	1.086481	0.317039	7.35487	1.741452	**0**	**0**
F5	9.9406	0.1625	27.86558	0.763626	96.71832	60.11559	67.54309	62.22534	**0**	**0**
F6	0.0013709	0.0038467	3.116266	0.532429	0.000102	8.28e-05	2.5e-16	1.74e-16	**0**	**0**
F7	**2.9026e-05**	**0.001073**	0.001425	0.001149	0.122854	0.044957	0.089441	0.04339	70.00463	0.0012
F8	**-12569**	**193.8**	-5080.76	695.7968	-4841.29	1152.814	-2821.07	493.0375	-11080.1	574.7
F9	**0**	**0**	**0**	**0**	46.70423	11.62938	25.96841	7.470068	69.2	38.8
F10	**8.8818e-16**	**2.0512e-15**	7.4043	9.897572	0.276015	0.50901	0.062087	0.23628	9.7e-08	4.2e-08
F11	**0**	**0**	0.000289	0.00158	0.009215	0.007724	27.70154	5.040343	**0**	**0**
F12	0.0014063	0.0013841	0.339676	0.214864	0.006917	0.026301	1.799617	0.95114	**7.9e-15**	**8e-15**
F13	0.035629	0.012551	1.889015	0.266088	0.006675	0.008907	8.899084	7.126241	**5.1e-14**	**4.8e-14**
F14	0.00040263	**8.1233e-05**	0.000572	0.000324	0.000577	0.000222	0.003673	0.001647	**4.5e-14**	0.00033
F15	**0.39789**	5.9489e-05	0.397914	2.7e-05	**0.39789**	**0**	**0.39789**	**0**	**0.39789**	9.9e-09
F16	**3**	3.5077e-05	**3**	4.22e-15	**3**	**1.33e-15**	**3**	4.17e-15	**3**	2e-15
F17	-3.8624	0.0037661	-3.85616	0.002706	**-3.8628**	**2.58e-15**	**-3.8628**	2.29e-15	N/A	N/A
F18	**-3.3533**	**0.01788**	-3.2202	0.098696	-3.26634	0.060516	-3.31778	0.023081	N/A	N/A
F19	**-10.454**	0.81151	-8.18178	3.829202	-8.45653	3.087094	-9.68447	2.014088	-10.403	**3.9e-07**
F20	**-10.536**	0.08496	-9.34238	2.414737	-9.95291	1.782786	**-10.536**	**2.6e-15**	**-10.536**	1.9e-07

Table 5. Datasets Description

Dataset	Attribute no.	Instances no.	Classes no.
Australian	14	690	2
German Credit	24	1000	2
Sonar	60	208	2
Zoo	17	101	7
NSL-KDD	41	5960	4
Diabetic	19	1151	2
Heart Disease	13	270	2
Segment	19	2310	7
Liver Disorders	6	345	2

Table 6. Performance Results of IRaWOA, GA, PSO and ACO attribute Selection algorithm on different Datasets

Dataset		IRaWOA	WOA	GA	PSO	ACO
Australian	Av_Acc	**0.8637**	0.8256	0.8289	0.8246	0.8390
	Std	**0.0201**	0.0202	0.0228	0.0731	0.0240
	Best_Acc	**0.8846**	0.8656	0.8553	0.8744	0.8530
German Credit	Av_Acc	**0.7436**	0.7140	0.7133	0.6889	0.7081
	Std	**0.0054**	0.0367	0.0200	0.0207	0.0168
	Best_Acc	**0.7510**	0.7490	0.7451	0.7333	0.7240
Sonar	Av_Acc	**0.8942**	0.8543	0.7540	0.7857	0.8130
	Std	**0.0126**	0.0341	0.0691	0.0346	0.0255
	Best_Acc	**0.9231**	0.9188	0.8720	0.8571	0.8751
Zoo	Av_Acc	**0.9998**	0.9569	0.8550	0.9512	0.9406
	Std	**0.0005**	0.0278	0.0690	0.0646	0.0324
	Best_Acc	**0.9999**	0.9647	0.9601	0.9714	0.9730
NSL-KDD	Av_Acc	**0.9540**	0.9318	0.9051	0.9241	0.9260
	Std	**0.0009**	0.0214	0.0349	0.0251	0.0351
	Best_Acc	0.9550	0.9408	0.9252	**0.9581**	0.9411
Diabetic	Av_Acc	0.6931	0.6031	**0.7504**	0.6931	0.6451
	Std	**0.0151**	0.0393	0.0169	0.0347	0.0394
	Best_Acc	0.7049	0.6231	**0.7748**	0.6897	0.6681
Heart Disease	Av_Acc	**0.8296**	0.7633	0.7801	0.7700	0.8260
	Std	**0.0037**	0.0209	0.0210	0.0360	0.0240
	Best_Acc	0.8444	0.7801	**0.9102**	0.9059	0.8871
Segment	Av_Acc	**0.9716**	0.9515	0.9150	0.9431	0.9152
	Std	**0.0019**	0.0043	0.0177	0.0147	0.0167
	Best_Acc	**0.9723**	0.9605	0.9515	0.9521	0.9462
Liver Disorders	Av_Acc	**0.7289**	0.7004	0.6780	0.7030	0.6120
	Std	**0.0014**	0.1185	0.0524	0.1263	0.0460
	Best_Acc	**0.7589**	0.7354	0.7373	0.7573	0.6551

Table 7. SVM Comparison Results of IRaWOA attribute selection Algorithm on different Datasets

Dataset	All		WOA		IRaWOA	
	Attributes no.	F-measure	Attributes no.	F-measure	Attributes no.	F-measure
Australian	14	0.5565	8	0.6985	4	0.8521
German Credit	24	72.400	12	0.7450	12	0.7830
Sonar	60	0.6346	38	0.6682	25	0.6875
Zoo	17	0.9108	12	0.9307	5	0.9701
NSL-KDD	41	0.7698	28	0.8602	18	0.9573
Diabetic	19	0.5690	15	0.6342	6	0.7149
Heart Disease	13	0.5592	9	0.8333	7	0.8370
Segment	19	0.6450	13	0.8082	5	0.9730
Liver Disorders	6	0.5942	4	0.6010	4	0.7971

Table 8. J48 Comparison Results of IRaWOA attribute selection Algorithm on different Datasets

Dataset	All		WOA		IRaWOA	
	Attributes no.	F-measure	Attributes no.	F-measure	Attributes no.	F-measure
Australian	14	0.8565	8	0.8362	4	0.8790
German Credit	24	72.200	12	0.7240	12	0.8280
Sonar	60	0.7115	38	0.7115	25	0.8903
Zoo	17	0.9207	12	0.9209	5	0.9603
NSL-KDD	41	0.9582	28	0.9798	18	0.9817
Diabetic	19	0.6359	15	0.6299	6	0.7132
Heart Disease	13	0.7778	9	0.8296	7	0.8481
Segment	19	0.9645	13	0.9636	5	0.9822
Liver Disorders	6	0.6869	4	0.6289	4	0.8459

Table 9. NB Comparison Results of IRaWOA attribute selection Algorithm on different Datasets

Dataset	All		WOA		IRaWOA	
	Attributes no.	F-measure	Attributes no.	F-measure	Attributes no.	F-measure
Australian	14	0.7710	8	0.7637	4	0.8681
German Credit	24	75.500	12	0.7330	12	0.7930
Sonar	60	0.6682	38	0.6923	25	0.7269
Zoo	17	0.96039	12	0.9505	5	0.9801
NSL-KDD	41	0.6355	28	0.6012	18	0.6432
Diabetic	19	0.5638	15	0.5656	6	0.5912
Heart Disease	13	0.8518	9	0.8259	7	0.8848
Segment	19	0.8038	13	0.7969	5	0.8709
Liver Disorders	6	0.5536	4	0.4986	4	0.6246

VI. Conclusion

This paper proposed a modified bio-inspired algorithms named RaWOA based on WOA algorithm. In the proposed RaWOA, reciprocal spiral is adopted to simulate the spiral updating position of the WOA bubble-net behavior. Twenty benchmark optimization functions were employed to asses and verify the performance of the proposed RaWOA algorithm. Experimental results illustrates that the proposed RaWOA algorithms provide highly competitive results, due to fewer chances to get stuck at local minima and its fast convergence. Moreover, this paper proposed IRaWOA a wrapper attribute selection algorithm. Whereby, information gain is integrated to guarantee a large initialization for the IRaWOA algorithm. Results on nine UCI datasets reveals that the proposed IRaWOA is able to outperform three well-known attribute selection algorithms; PSO, GA and ACO in the literature.

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