Comparative Analysis of Improved Cuckoo Search(ICS) Algorithm and Artificial Bee Colony (ABC) Algorithm on Continuous Optimization Problems

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***Abstract*—This work is related on two well-known algorithm, Improved Cuckoo Search and Artificial Bee Colony Algorithm which are inspired from nature. Improved Cuckoo Search (ICS) algorithm is based on Lévy flight and behavior of some birds and fruit flies and they have some assumptions and each assumption is highly observed to maintain their characteristics. Besides Artificial Bee Colony (ABC) algorithm is based on swarm intelligence, which is based on bee colony with the way the bees maintain their life in that colony. Bees' characteristics are the main part of this algorithm. This is a theoretical result of this topic and a quantitative research paper.**

Keywords—Artificial Bee Colony (ABC) algorithm; Bioinformatics; Improved Cuckoo Search (ICS) algorithm; Lévy flight; Meta heuristic; Nature Inspired Algorithms

I. Introduction

Beautiful nature is full of surprises and mystery. People have learnt a lot from the Mother nature. By analyzing symptoms people manage to reveal the mystery of nature. As time changes, humans also change their characteristics and their behavior to the nature. Now a day's people find solutions of their daily life problems with the help of nature and that is known as meta-heuristic solutions. The bee colony and the improved cuckoo search algorithm elevate the eco-life system in a new level. On the basis of key functions and iteration number, the comparison between Artificial Bee Colony and Improved Cuckoo Search algorithm is done. Artificial Bee Colony works on the optimization algorithm introduced by D. Karaboga[1]. And the Improved Cuckoo Search algorithm is extended to more complicated cases in which each nest has multiple eggs representing a set of solutions[2][3][4]. Within last few decades, dozens of meta-heuristic algorithms are published and still been publishing. Among them Bat [5][6], Firefly [7][8], Flower Pollination [9], Artificial Bee Colony [10], Improved Artificial Bee colony [11], Ant Colony [12], Cuckoo search [13] is highly recommended algorithms. The algorithms which have mentioned above are upgrading day by day. So, here it has been focused on the implementation and the operations of the iteration number, and the tested functions for both algorithms that mentioned above are same. For preparing this research, first of all, the data of mean and median for improved cuckoo search have been measured and the algorithm is obtained. Then the comparison makes them different from each other. By producing graphical outcome, it is observed that improved cuckoo search is good enough. Improved cuckoo search (ICS) & its algorithm is being described in section II. Then in section IV the artificial bee colony (ABC) is being described with its algorithm. After that in section V the simulation & analysis part is being described and then the findings in section VI. Finally, in section VII the total work is being summarized in short in the conclusion.

II. Cuckoo Search

A. Basic Ideas of Cuckoo Search

Cuckoo Search (CS) is used to solve optimization problems which are a meta–heuristic algorithm, developed by 'Xin-She Yang' that is based on the manner of the cuckoo species with the combination of Lévy flight behavior of some birds and fruit flies [14][15]. The inspiration behind developing Cuckoo Search Algorithm is the invasive reproductive strategy and the obligate brood parasitism of some cuckoo species by laying their eggs in the nest of host birds [16]. Some female cuckoo like Guira and Ani can copy the patterns and colors of few chosen host species. This imitates power is used to increase the hatching probability which bring their next generation. The cuckoo has an amazing timing of laying eggs. Parasitic cuckoos used to choose a nest where the host birds lay their own eggs and it takes less time to hatch cuckoo's egg than the host bird's eggs. After hatching the first egg, the first instinct, action is to throw out the host eggs or to propel the eggs out of the nest to ensure the food from the host bird.

B. Basic Points of Cuckoo Search

Each Cuckoo's egg in a nest illustrates a new solution. The aim of Improve Cuckoo Search is to serve the new and potentially better solutions to replace the previous solutions in the Cuckoo Search. The algorithm can be extended to more complicated cases in which each nest has multiple eggs that represent a set of solutions. The CS is based on three idealized rules that are given bellow:

1) Each cuckoo lays one egg at a certain time, and dumps it in a nest which is randomly chosen [17].

2) The best nests provide high quality of eggs (solutions) that will carry over to the next generations [17].

3) A host bird can discover an alien egg from his nest with probability of $Pa \in [0, 1]$. In this case, the host bird can *either throw the egg away or abandon or can completely build a new nest in a new location [17].*

C. Lévy Flights

Generally, the foraging path of an animal is successful a random walk as the next step is based on both the current location and the transition probability to the next location. The chosen direction implicitly depends on a probability, which can be modeled mathematically. The flight behavior of many animals and insects demonstrates the typical characteristics of Lévy flights. A Lévy flight is a random walk in which the step-lengths are distributed according to a heavy probability distribution. After a large number of steps, the distance from the origin of the random walk tends to a stable distribution [17][18].

III. IMPROVED CUCKOO SEARCH (ICS)

A. Characteristics of Improved Cuckoo Search

The parameters Pa, λ and α introduced in the CS, help the algorithm to find globally and locally improved solutions, respectively. The parameters Pa and α is very important parameters in fine-tuning of solution vectors, and can be potentially used to adjust the convergence rate of the algorithm. The traditional CS algorithm uses a fixed value for both Pa and α. The key difference between ICS and CS is the way of adjusting Pa and α. To improve the performance of CS algorithm and eliminate the drawbacks lies with fixed values of Pa and α, the ICS algorithm uses variables Pa and α. The values of Pa and α dynamically change with the number of generations and have been expressed in equations 1-3, where NI and gn are the number of total iterations and the current iteration respectively.

$$P_a(g_n) = P_{a\,max} - \frac{g_n}{NI}\,(P_{a\,max} - P_{a\,min}) \quad (1)$$

$$\alpha\,(g_n) = \alpha_{max}\exp(c.\,g_n) \quad (2)$$

$$c = \frac{1}{NI} L_n\,(\frac{\alpha_{min}}{\alpha_{max}}) \quad (3)$$

B. Algorithm of ICS

Begin

Objective function f(x), $x = (x_1, ..., x_d)^T$;
Initial a population of *n* host nests xi (i = 1, 2, ..., n);
while (t<MaxGeneration) or (stop criterion)
Get a cuckoo (say i) randomly by *Lévy* flights;
Evaluate its quality/fitness F_i;
Choose a nest among *n* (say j) randomly;
if(F_i>F_j) Replace j by the new solution; *end*
A fraction (P_a) of worse nests are abandon and new once are built.
Keep the best solutions (or nests with quality solutions);
Rank the solutions and find the current best;
end while
Post-process results and visualization;

End

When generating new solutions X_i (t +1) for the i^th cuckoo, the following Lévy flight is performed

$$X_i(t+1) = X_i(t) + \alpha \oplus \text{Lévy}\ (\lambda) \quad (4)$$

Where α>0 is the step size, which should be related to the scale of the problem of interest. The product ⊕ means an entry-wise multiplications. According to Yang's research work, it has considered that a *Lévy* flight in which the step-lengths are distributed according to the following probability distribution

$$\text{Lévy u} = \text{t}^{-\lambda},\ 1 < \lambda \leq 3 \quad (5)$$

This has an infinite variance. Here, the consecutive steps of a cuckoo essentially form a random walk process which obeys a power law step length distribution with a heavy tail.

It is worth pointing out that, in the real world, if a cuckoo's egg is very similar to a host's egg, then this cuckoo's egg is less likely to be discovered, thus the fittest should be related to the difference in solutions. Therefore, it is a good idea to do a random walk in a biased way with some random step sizes.

IV. ARTIFICIAL BEE COLONY (ABC)

A. Basic Ideas of Artificial Bee Colony (ABC)

The ABC algorithm is of wide range of insects that are dependent and meta-heuristic algorithm that is developed on the provision behavior of honey bee colonies [19]. The ABC is an algorithm which describes the intelligent provision behavior of honey bee swarms. It is simple, vigorous, strong and healthy and population dependent randomly determined optimization algorithm [20]. The ABC algorithm which may be used for explanation of multidimensional and multimodal optimization matters [21].

B. Some Common Mistakes

- In ABC, honey bees are classified into three groups that are named as employed bees, onlooker bees and scout bees.
- The employed bees are the bee which searches for the food source and gather the information about the quality of the food source.
- Onlooker bees stay in the hive and search the food sources on the basis of the information gathered by the employed bees.
- The scout bee, searches new food sources randomly in places of the abundant food sources.

C. Algorithm of ABC

1) Algorithm 1 Artificial Bee Colony Algorithm

Initialize the parameters;

While Termination criteria is not satisfied do

Step 1: Employed bee phase for computing new food sources.

Step 2: Onlooker bees phase for updating the location of food sources based on their amount of nectar.

Step 3: Scout bee phase for searching about new food sources in place of rejected food sources.

Step 4: Memorize the best food source identified so far.

End of while

Output The best solution obtained so far.

2) Algorithm 2 Solution update in Employed bee phase

Input: solution x_i, $prob_i$ and $j \in (1, D)$;
for $j \in \{1 \text{ to } D\}$ do
  if $U(0, 1) > prob_i$ then
    $v_{ij} = x_{ij} + \varphi_{ij}\ (x_{ij} - x_{kj}) + \psi_{ij}\ (x_{best\,j} - x_{ij})$;
  else
    $v_{ij} = x_{ij}$;
  end if
end for

V. Simulation and Analysis

A. GRAPH with Parameter settings

In this paper, 70 independent runs on each algorithm to get the result from the test functions which are rowed in Table-1. The population for each function is set for 14. Maximum cycle has been used 70 for both algorithms. And the Dimension for each function for each algorithm are set for D=5, 10, 15, 25 respectively. Of ICS, we use Pa, α, λ for improved the result for ICS globally and locally. Here in ABC Pa=0.25, αmin=.05, αmax=0.5. Finding the best, worst, mean, median and Standard deviation value for both algorithms is the main goal. On the basis of the result of finding the best and new place as well as nest or colony the3D surface and mesh are simulated for Rosen rock function, Ackley functions have shown in two views. In X-axis the objective value and in Y-axis two variable values is plotted. For this MATLAB R2013a version is used for simulation with 4th generation Intel i5 processor 2.7GZ with 4GB RAM of PC.

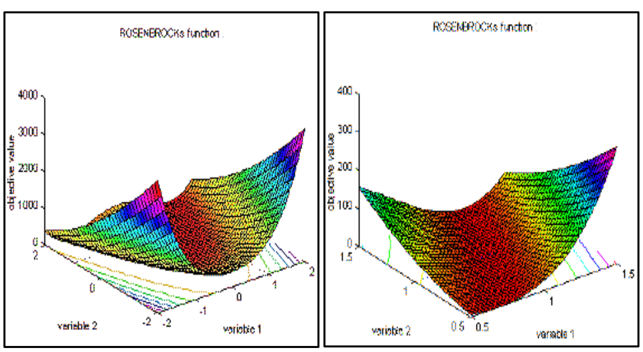

Fig. 1. 3D surface plots (2 view) of Rosenbrock function that best for ICS

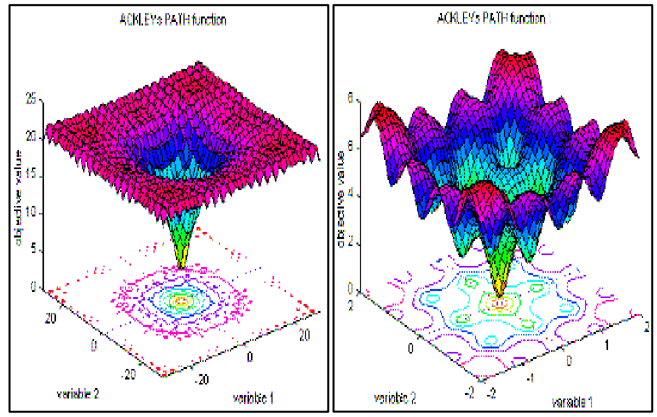

Fig. 2. 3D surface plots (2 view) of Ackley function that best for ICS.

VI. Findings

In ABC algorithm the fitness and global min is compared with ICS algorithm. The work has mainly focused on the differences between these two algorithms and its basis on the mean value and on the basis of time. It is true that, if the exploitation is too high and the exploration is too low, then algorithms may trap into locally optimal points. So, some methods are followed and tried to avoid any kinds of trap that may cause trouble. Because this could affect find the global optimum. Or if the exploration is too high and exploration is too low than exploration then the convergence speed will decrease. In the ABC algorithm we use population for about 14 and tested in f1, f2, f3, f4, f5, f6 functions with runtime 70 for both ABC and ICS algorithm. When the dimension increases ABC gives poorer results than ICS but gives good result in lower dimensions. That means ICS gives the best result in high Dimension. So, it can be said that ABC works well in exploitation, but in the exploration it works poorly. But ICS works better in exploration. In this experiment ICS shows better results for dimension 10 and 25.For dimension 10, the ICS gives better result than ABC for f1, f3, f4, f5 functions on the basis of the mean value. And for dimension 25 ICS gives better result for f1, f3, f4, f5. And for other two dimensions, it works equally as ABC. Among these functions Rosenbrock gives the best result for ICS. Basically, in ICS cuckoo search his food within a wide range of area, not in a limited range of area. That means its food area is large. On the other hand In ABC a bee only finds its honey on its own place where the least and maximum capacity honey holder bees are present .If the bee fails to find honey from other sources that has the maximum capacity of honey than the bee turns back and looks for other bees that has the maximum amount of honey [22][23][24].

TABLE I. BENCHMARK FUNCTIONS USED IN THE EXPERIMENTAL STUDIES. HERE, D: DIMENSIONALITY OF THE FUNCTION, S: SEARCH SPACE, C FUNCTION CHARACTERISTICS WITH VALUES — U: UNIMODAL AND M: MULTIMODAL

func	Name	D	C	S	Function Definition	$f_{\min}$
f1	Sphere	5,10,15,25	U	[-5.12, 5.12]D	$f(x) = \sum_{i=1}^{d} x_i^2$	0.0
f2	Griewank	5,10,15,26	M	[-15, 15]D	$f(x) = \frac{1}{4000}\sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d} \cos\frac{x_i}{\sqrt{i}} + 1$	0.0
f3	Rastrigin	5,10,15,27	M	[-15, 15]D	$f(x) = \sum_{i=1}^{d}[x_i^2 - 10\cos(2\pi x_i) + 10]$	0.0
f4	Rosenbrock	5,10,15,28	U	[-15, 15]D	$f(x) = \sum_{i=1}^{d-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	0.0
f5	Ackley	5,10,15,29	M	[-32, 32]D	$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\right) + 20 + e$	0.0
f6	Schwefel	5,10,15,25	M	[-500, 500]D	$f(x) = 418.9829 * d - \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	0.0

TABLE II. COMPARISON BETWEEN ABC & ICS ON 6 STANDARD BENCHMARK FUNCTIONS. ALL ALGORITHMS ARE RUN 24 DIFFERENT TIMES ON EACH OF THE FUNCTIONS. THE BEST RESULT FOR EACH FUNCTION WITH EACH DIMENSION IS MARKED BOLD

func	Name	Algorithm	Dim	Best	Worst	Mean	Median	SD
f1	Sphere	ABC	5	1.42E-15	4.02E-12	**6.78E-13**	4.04E-14	2.10E-12
		ICS		6.90E-02	2.00E+00	1.00E+00	9.32E-01	7.92E-01
		ABC	10	0.0011	396.638	59.95378571	0.6839	137.54161
		ICS		0.0562095	6.667	**2.399571888**	0.475504	3.02238008
		ABC	15	8.15E-07	0.406	**0.077864353**	0.0018	0.21592723
		ICS		0.0515647	11.4665	3.957276326	0.353732	5.31127886
		ABC	25	2.8065	4808.4	1494.409743	882.56	2418.11741
		ICS		0.053437	9.13084	**3.194834213**	0.400225	4.19977765
f2	Griewank	ABC	5	0.0099	0.1052	**0.041857143**	0.0296	0.04682883
		ICS		0.0622457	3.70203	1.476183907	0.664273	1.59298316
		ABC	10	0.0197	0.2396	**0.0757**	0.0557	0.0693187
		ICS		0.0569547	6.15002	2.234685552	0.497087	2.77257803
		ABC	15	0.0322	0.1881	**0.073914286**	0.0375	0.09214291
		ICS		0.0596114	4.6883	1.775403562	0.578299	2.0705851
		ABC	25	0.9752	4.1287	**1.953914286**	1.1097	1.76112841
		ICS		0.0516801	11.3016	3.903275186	0.356502	5.23291644

f3	Rastrigin	ABC	5	8.79E-10	1.0087	**0.428446591**	0.00012567	0.75568014
		ICS		0.05697	6.13833	2.230957736	0.497574	2.76877797
		ABC	10	3.57E-11	7.44E+09	1298.930031	0.0777	3180.44622
		ICS		0.0669566	2.39661	**1.103110736**	0.845762	0.96833078
		ABC	15	2.0855	10.7955	6.661642857	7.5693	2.8464014
		ICS		0.0556383	7.09699	**2.537333517**	0.45937	3.22837601
		ABC	25	0.9989	9.4733	4.462328571	3.7386	4.27762977
		ICS		0.0553482	7.34006	**2.61550469**	0.451101	3.34467278
f4	Rosenbrock	ABC	5	4381.7	95705	19810.21429	8493.5	47395.5977
		ICS		0.0534698	9.09728	**3.183930407**	0.401039	4.18377811
		ABC	10	570.316	2.27E+07	4704766.516	767.163	8153588.31
		ICS		0.0547036	7.88175	**2.790039516**	0.433669	3.60370266
		ABC	15	25.9912	9.64E+09	1376914539	254.39	5151941350
		ICS		0.0518323	11.1223	**3.844661369**	0.359818	5.14762771
		ABC	25	0.2996	6459.9	962.3464143	68.6211	3428.69951
		ICS		0.051982	10.914	**3.77656329**	0.363682	5.04855246
f5	Ackley	ABC	5	1.67E+01	20.0102	19.53458571	20	1.74778989
		ICS		0.935065	12.2685	**5.024255357**	1.86915	5.13666397
		ABC	10	20	21.2061	20.31675714	20.0979	0.44159039
		ICS		0.0689939	2	**3.002425739**	0.933432	2.15179115
		ABC	15	20	20.4971	20.09742857	20.0045	0.26100873
		ICS		0.0563243	6.58119	**2.372110814**	0.478821	2.98126045
		ABC	25	20.0354	21.5963	20.4319	20.3623	0.77635362
		ICS		0.0530613	9.54667	**3.330121363**	0.39063	4.39792509
f6	Schwefel	ABC	5	-318.175	14.2288	**-238.4171**	-252.299	166.583262
		ICS		0.0615128	3.94352	1.548055762	0.639132	1.71018618
		ABC	10	-577.248	-599.325	**-690.0644574**	-607.041	88.8336281
		ICS		0.0602585	4.39303	1.684305824	0.599625	1.92797598
		ABC	15	-917.593	-864.837	**-931.2613**	-944.684	45.1666012
		ICS		0.0535746	8.98318	3.146848581	0.403787	4.12938848
		ABC	25	-1590.9	-693.199	**-1457.342729**	-1581.6	476.567607
		ICS		0.0515618	0.353507	3.968892143	0.353507	5.32786014

On the X-axis the number of generations and in Y-axis fitness is set and plot this graph (fig-3). From this graph the comparison is clarified clearly.

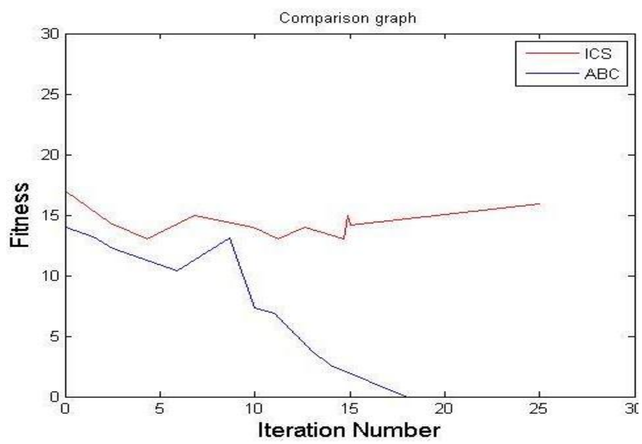

Fig. 3. 2D plot of ICS vs ABC algorithm

VII. Conclusion

a) This paper represents the comparative study between swarm intelligence base and Lévy flight behavior base algorithms the Artificial Bee Colony (ABC) algorithm [1] and the Improved Cuckoo Search (ICS) algorithm [2][3][4].Optimization results in the standard benchmark problems for Artificial Bee Colony (ABC) algorithm and Improved Cuckoo Search (ICS) algorithm exhibit the effective results and competitive results of the algorithms. The main reason of the performance difference is basically in ICS where cuckoo search his food within a vast area rather than limited. On the contrary, in ABC a bee only finds its own light in its own place even though the light holder bees are present which have the minimum and maximum intensity of light. And if the bee fails to find from others that hold the highest capacity of light, then it turns back and search for other bees which have the larger intensity of light. And its place is limited not wide while searching for bees. So, that means cuckoo works on a wide range of area and it needs more dimension than ABC. On the other side, ABC needs fixed area to search its best. Last of all, it can be assumed that ICS and ABC can be improved more than before in the future.

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