A NOVEL HYBRID BAT CROW SEARCH ALGORITHM FOR SOLVING OPTIMIZATION PROBLEMS

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ABSTRACT

Meta heuristic algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and other algorithms are great and famous techniques used to solve many hard and complex optimization problems. This paper presents a new hybrid algorithm named Hybrid Bat Crow Search Algorithm (HBCSA). To achieve this algorithm, two algorithms were considered. The algorithms are Crow Search Algorithm (CSA) and Bat Algorithm (BA). The advantageous points of the two algorithms were taken into consideration and used to design an effective hybrid algorithm that can give significantly high performance in many benchmark functions. In addition, quantum behaved PSO equation is used in this hybrid algorithm. This leaded to better results when testing the algorithm against Benchmark problems. The combination of concept and functionality of Bat and Crow algorithms enable the suggested hybrid algorithm of making an appropriate trade-off between exploration and exploitation capabilities of the new algorithm.

For the purpose of evaluating the performance of the new Hybrid Bat Crow Search Algorithm (HBCSA), some well known Benchmark functions were utilized. In the new algorithm every member in the swarm will have behave like a crow in the sense of observing other members in the swarm to see where they hide their foods. In the same time, as in bats, every member will use echo system while searching its own solution. Echo system is integrated with PSO equations. Each member has an awareness parameter as in CSA. According to awareness parameter a member can know whether if another member is following it or no. These are the basic lines of the new HBCSA. The results indicated that the proposed HBCSA can produce very competitive solution when compared to other famous and state of the art meta-heuristic algorithms.

Key Words: Meta-Heuristic, Crow Search Algorithm, Bat Algorithm, Benchmark Functions.

1. INTRODUCTION

Nowadays researchers deal with hard and complex problems. Solving complex problems using traditional techniques is sometimes impossible because of the complexity of the problems. That's why many researchers aimed to develop novel solution approaches named meta heuristics for solving complex and hard optimization problems in reasonable cost and time. Meta heuristics, due to their advantages, become very popular and applied to solve complex real-world problems [1, 2]. The basic idea for most of the meta heuristic algorithms is inspiration from the behaviour of living animals in nature, nature or physical phenomena [3, 4] divides meta heuristics in three main categories: Evolutionary based, Physics based and Swarm based techniques.

In general, with using the powerful sides of different existing algorithms, a new better algorithm can be developed which can use advantages of the other algorithms to perform better. Hybrid algorithm in general is efficient from the original versions of the algorithms which was taken from. This is due to the fact that the hybrid algorithm benefits from all the advantages of the original algorithms [3-5].

In this research, a novel hybrid algorithm is proposed based on two proposed meta heuristic algorithms of Bat Algorithm and Crow Search Algorithm. The new hybrid algorithm is named Hybrid Bat Crow Search Algorithm (HBCSA). The proposed hybrid algorithm benefits from advantages of both algorithms and aims to fill their drawbacks. The modifications considered in this research result in a very efficient algorithm which performs significantly better than the basic version of the two algorithms. To evaluate the effectiveness of the new algorithm, well-known benchmark functions are utilized, and the results are compared to other state-of-the-art algorithms.

2. RELATED WORKS

2.1. BAT ALGORITHM (BA)

Bats have great features and they are amazing. They are mammals and they have wings. Bats also have great echolocation ability. The pulses that bats emit differ in properties and these pulses are related to their hunting tactics and depending on the specie of the bat. Their signal bandwidth differs according to the species, and in general, it increases by using more harmonics [6].

In simulations, virtual bats are used. Rules have to be defined on the position x(i) and velocity v(i) in a d dimensional searching space and they are updated according to them. The new solutions x_i^t and velocities v_i^t at time step t are given by [6, 7]:

$$fi = fmin + (fmax - fmin)\beta \quad (1)$$

$$v_i^t = v_i^{t-1} + (x_i^t - x*)fi \quad (2)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (3)$$

where β ∈ [0,1] is a random valued vector computed using uniform distribution. Here $x*$ is the present global best solution (location) which is computed after looking at all the solutions of all the bats in the swarm. fi is the velocity increment.

The loudness value A(i) and the plus emission rate r(i) have to be updated while the algorithm iteration proceeds as follow [6, 7]:

$$A_i^{t+1} = \alpha A_i^t, \; r_i^{t+1} = r_i^0[1 - \exp(-\gamma t)] \quad (4)$$

Taking into consideration that:

$A_i^t \to 0, r_i^t \to r_i^0, as\ t \to \infty$

2.2. CROW SEARCH ALGORITHM (CSA)

Crows are known for their cleverness and can communicate in a sophisticated manner, remember faces and use tools. That is why they have been recognized as one of the most intelligent animals found on the planet. The main concept behind the algorithm is that crows store their surplus food secretly at secret location and retrieve it whenever needed. They can recall their food hiding places even after several months. Crows observe food hiding places of other birds and steal their food. To find the food hiding locations of crows is a hard task to do as they can make fool the watching and following crows by going to other location in case, they know that someone is following [9].

In the crow search algorithm, each crow will update its own position according to awareness of the other crow that it may follow. For example, let's assume two crows i and j. Crow i will follow crow j to find the hiding food by crow j and steal the food. For this, crow i will update its position according to the following formula [8, 9].

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times fl_i^t \times \left|m_i^t - X_i^t\right|, & ri \geq AP_i^t \\ a\ random\ position\ otherwise \end{cases} \quad (5)$$

Where AP_i^t is the awareness of crow j and fl_i^t is the flight length of crow i. In other words, if crow j feels that crow i is following him, crow i updates to a random place in solution space. It is worth noting that for a crow i, a crow j is picked in random way and is used to update its position [8, 9].

2.3. PROPOSED HYBRID MODEL

In the new algorithm, every member in the swarm will have behave like a crow in the sense of observing other members in the swarm to see where they hide their foods. In the mean while as in bats, every member will use echo system while searching its own solution. Echo system is integrated with particle swarm optimization equations. Each member has an awareness parameter as in CSA. According to awareness parameter a member can know whether if another member is following it or no. Member j may not know that member i is following it. due to that, crow i approaches to the hiding place of crow j. Member j may know that member i is following it. due to that, and for the purpose of protecting the food it hid from being stolen, member j will trick member i by changing its course and moving to another position of the search space. A member will use echo system alongside with quantum behaved particle swarm optimization equations to locate best food (solution) place [11]. In the same time, it will keep an eye on foods place (solutions) found by the others it follows. According to them its new location in the search space is defined. In addition, local search is applied so every member will try to improve its own solution by looking to nearby solutions. This help in exploration phase of the algorithm.

Below is the pseudo code of the proposed algorithm:

```
Initialize positions of the flock in the swarm (N) in the search space in random way
For each member Evaluation is made of its position
Set the initial values of memories for the members in the swarm
Calculate the objective function for each member.
while current iteration < total iterations number
            for i = 1 → N (all N member of the swarm)
              Choose one of the members to follow (j for example) randomly.
              Define an awareness probability
              If (random value >= AP)
    Generate new solutions by using quantum behaved particle swarm optimization equations.
                And approach the member j position.
              else
                generate a new position randomly
              end
              With a randomly generated probability generate a local solution near the best solution.
            end for
            foreach member in the swarm
              Check whether the solution found by the member j is better and update solution
            end foreach
            if (rand < A(i) & f(xi ) < f(x∗))
                        The new generated solution is taken
                        Increase ri and reduce Ai
            End
            If solution doesn't does not improve after defined number of steps
Initialize the loudness values of Ai and reset pulse rates ri
end while
Process and visualize the acquired results
```

3. RESULTS AND DISCUSSION

Meta heuristics are stochastic algorithms thus, several Benchmark functions are needed to be solved to ensure the efficiency of the algorithms. In this research, many benchmark functions were used to evaluate the performance of the proposed HBCSA against well-known meta heuristic algorithm in exploration and exploitation abilities. For validating the efficiency of the proposed hybrid algorithm, the performance of HBCSA is compared to CSA and BA, as well as other well know algorithms. Average values are used to compare results.

For comparison made in Table 1, all the algorithms were compared using the same set of parameters. Number of runs of each algorithm was set to 2000 iterations, decision number variables (dimension) is set to 10 and population size is set to 20.

For comparison made in Table 2, number of runs of each algorithm was set to 2000 iterations, decision number variables (dimension) is set to 10 and with population size is set to 50. Table1 and Table 2 are showing the results of comparing the proposed HBCSA with CSA, BA and an Improved Bat Algorithm (IBA) respectively [6-10].

Table 1: Comparing HBCSA with Crow Search Algorithm.

Benchmark Functions	FMIN	HBCSA	CSA
		AVERAGE	
F1: Sphere	0	**1.10E-117**	4.09E-11
F2: Rosenbrock	0	**3.2731**	10.86
F3: Griewank	0	**0.11141**	0.21
F4: Schwefel	0	**1.49E-74**	6.27E-03
F5: Ackley	0	**4.56E-15**	1.9

Table 2: Comparing HBCSA with BA and IBA.

Benchmark Functions	FMIN	HBCSA	BA	IBA
		AVERAGE		
F1: Sphere	0	**1.41E-284**	7.90E-01	8.11E-06
F2: Zakharov	0	**1.20E-298**	3.38E+01	4.63E-03
F3: Sum of Different Power	0	**0**	2.72E-03	5.38E-06
F4: Dixon-Price	0	**0.66667**	7.90E+01	**0.66667**
F5: Step	0	**5.20E-19**	7.90E+01	6.67E-01
F6: Michalewicz	-9.66015	**-8.2989**	-5.16	-7.91
F7: Griewank	0	**0.12181**	1.14E+01	1.34
F8: Easom (d=2)	-1	**-1**	-3.25E-02	-9.99E-01
F9: Perm (d=4)	0	9.66E-02	3.54E-01	**7.16E-02**
F10: Six Hump Camel Back (d=2)	-1.0316	**-1.0316**	-1.03093	**-1.0316**

From the results, it is clear that the proposed hybrid algorithm performs significantly better than two meta-heuristic algorithms of BA and CSA. This is due to high exploration and exploitation ability of the proposed algorithm and this is normal due to the fact that the hybrid algorithm is made of these two algorithms and uses the best features of them.

The only exception was in Table 2 where the improved version of Bat Algorithm IBA was able to get a slightly better result in F9 Perm function. But HBCSA was again able to over perform at the other test benchmark functions.

A comparison is performed among HBCSA and other metaheuristic algorithms, and statistical analysis on simulation results is given in Table 3 [17]. These algorithms are Cuckoo Search Algorithm [12], Deferential Evolution Algorithm [13], Firefly Algorithm [14], Genetic Algorithm [15], Particle Swarm Optimization Algorithm [16]. The Benchmark functions are selected in such a way that they can assess the algorithm's ability to converge fast, jump out of local optima, ability to achieve a large number of local optima and avoid premature convergence. The average values obtained by the new hybrid algorithm and other algorithms on various test bed benchmark functions are listed in Table 3. The simulation results indicate that HBCSA generally gives very good performance compared with other algorithms.

For comparison made in Table 3, each algorithm was set to 10000 iterations, decision number variables was set to 30 (or based on the type of Benchmark function if 30 is not applicable) and population size was set to 50.

Table 3: Comparing HBCSA with other algorithms

Benchmark Functions	FMIN	HBCSA	CS	DE	FA	GA	PSO
		AVERAGE					
F1: Sphere	0	**5.70E-285**	6.489420E−61	2.61780E−165	7.86960E−04	2.20390E−02	1.76657E−51
F2: Beale	0	**0**	9.767450E−61	**0**	1.36830E−04	9.67890E−03	1.12460E−50
F3: Step	0	3.28E-16	1.22E+00	1.3000E−01	**0**	2.3026E−02	1.31167E−31
F4: Quartic function with noise	0	**1.03E-03**	1.24E+01	2.61590E−03	5.95780E−02	2.73870E−03	3.740E+00
F5: Bohachevsky	0	**0**	4.9218E−04	**0**	**0**	**0**	3.0393E−02
F6: Ackley	0	**5.86E-15**	1.71E+01	1.72E+00	7.7334E−04	4.6683E−02	1.82E+01
F7: Griewank	0	**0**	2.01E+01	9.220E−17	1.070E−07	5.55980E−02	4.05E+01
F8: Levy	0	**1.35E-31**	1.62E+01	5.9824E−02	1.20E+00	1.3732E−04	4.93E+00
F9: Michalewiz	−9.66015	-7.8322	−8.06E+00	−9.61550E+00	−8.88E+00	**−9.66E+00**	−7.750E+00
F10: Rastrigin	0	71.6037	1.08E+02	**1.25E+01**	3.47E+01	1.65E+01	1.45E+02
F11: Alpine	0	3.8031	1.06E+01	6.9E−16	1.19340E−02	**3.14740E−17**	4.44020E−02
F12: Schaffer	0	**0**	9.8155E−01	**0**	1.4304E−02	1.68965E−17	**0**
F13: Rosenbrock	0	**17.7875**	3.950E+01	2.360E+01	1.840E+01	3.79E+01	2.57E+02
F14: Easom	-1	**-1**	**-1**	**-1**	**-1**	**-1**	**-1**
F15: Shubert	− 186.7309	**− 186.7309**	**− 186.7309**	**− 186.7309**	**− 186.7309**	**− 186.7309**	**− 186.7309**
F16: Schwefel 2.21	0	0.27355	3.6728E−03	1.02E+00	**1.43170E−04**	4.66620E−02	1.0586E−01
F17: Schwefel 2.22	0	**4.10E-188**	1.12E+01	8.15E−91	1.50460E−03	5.43670E−02	7.28E+01
F18: Booth	0	3.50E-29	1.8174E−05	**0**	**0**	**0**	**0**
F19: Goldstein price	3	**3**	**3**	**3**	**3**	**3**	**3**
F20: Matyas	0	**0**	1.3308E−06	**0**	**0**	8.3889E−104	**0**
F21: Powell	0	**2.64E-07**	6.64E+00	1.31E+02	2.3957E−04	3.2713E−02	3.37E+03
F22: Power sum	0	1.66E-04	1.40150E−02	6.27360E−04	**1.29050E−04**	1.29970E−04	1.98390E−04

	The best result		Secondary best result

When the results of HBCSA are examined, it is noticed that HBCSA is reaching the optimal values in 8 functions of F2, F5, F7, F12, F14, F15, F19 and F20 and was better than most of the other algorithms in most of these functions. This indicates the efficiency of HBCSA. HBCSA was able to reach near optimal results in 7 functions of F1, F4, F6, F8, F13, F17 and F21 and its results was better than most of the other algorithms' results of the other algorithms used in comparison. In the others 7 functions of F3, F9, F10, F11, F16, F18 and F22 HBCSA couldn't get the best values comparing to other algorithms and the other algorithms reached better results than HBCSA. In general, the results prove the efficiency of HBCSA and that HBCSA performs significantly better than other meta-heuristic algorithms used in the comparison.

4. CONCLUSION

This paper presented a novel hybrid optimization algorithm named Hybrid Bat Crow Search Algorithm (HBCSA). It is population-based on the behaviour of crows and bats. In HBCSA, the control parameters are used to control the performance of the algorithm. Simulation results show that the performance of the proposed new algorithm is promising since it has produced competitive results in comparison with the other studied algorithms. On a set of benchmark functions, it is observed that although the other algorithms are known as fast techniques, they were outperformed by HBCSA at some benchmark functions. Due to the fact That the advantages of the two algorithms (BA and Crow Search Algorithm) are considered and utilize to design an efficient hybrid algorithm, this leaded to significantly better perform in various benchmark functions. In addition, quantum behaved PSO equation is used in this hybrid algorithm. This enhanced the results even more when testing the algorithm against Benchmark problems.

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