

A Review on Bat Algorithm

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Abstract—Complications of cracking real world glitches with their promising difficulties forced computer technologist to search for more skillful problem solving approaches. Meta-heuristic procedures are outstanding models of these methods and out of these the bat algorithm (BA) is a good example. BAT algorithm is found very efficient in solving difficult problems. This algorithm has been advanced hurriedly and has been practical in different optimization jobs. The literature has extended substantially since last seven years. This paper offers appropriate study of the various modifications of BAT algorithm.

Keywords— Artificial Bee Colony, Ant Colony Optimization, Bat Algorithm, Cuckoo Search Algorithm.

I. INTRODUCTION

Nature is an opulent source of motivation. Numerous scholars have been motivated by nature in several ways. So, many algorithms have been developed centered on the nature inspiration. Nowadays, nature inspired metaheuristic algorithms have become a good substitute for finding answer of firm optimization problems in real life. Some well-known nature inspired algorithms are as follows:

- Cuckoo search (CS) [1], inspired by the brooding behaviour of cuckoo species.
- Artificial bee colony algorithm (ABC) [2], based on the intelligent foraging behaviour of honey bee swarm.
- Particle swarm optimization (PSO) [3], inspired by the flocking behaviour of birds.
- Ant colony optimization (ACO) [4], based upon the foraging behaviour of ants.
- Termite colony optimization (TCO) [5] algorithm based upon intelligent behaviour of termites.
- Cat swarm optimization (CSO) [6], based upon the cat's behaviour.

This is not possible to cover all nature inspired metaheuristic algorithms in a single paper. Hence this paper is dedicated to the bat algorithm (BA). BA belongs to nature motivated swarm intelligence algorithms. Bat algorithm was proposed by yang in 2010 [7] and huge improvement has been done since last 7 years. The strategic goal of this revision is to review the BA and its enhancements in preceding years. The structure of this paper is as follows: section 2 discusses the basic BA, section 3 discusses the Modification of BA and last section concludes briefly.

II. BAT ALGORITHM

Bats are eye-catching animals and their higher potential of echolocation has engrossed interest of scholars from various arenas. Echolocation mechanism is a kind of sonar: bats, mainly micro-bats, create a loud and short pulse of sound and figure out the distance of an object by using the echo reruns back to their ears [8]. This remarkable positioning method makes bats being able to decide the difference between an obstacle and a prey, allowing them to hunt even in whole darkness [9].

Motivated by the conduct of the bats, Yang [7] has suggested a new meta-heuristic optimization method called Bat Algorithm. This method has been developed to behave as a band of bats searching for prey/foods using their proficiency of echolocation. In BA, the echolocation distinctiveness is idealized within the outline of the following rules by benefitting such features of bats:

All bats use echolocation to sense distance, and they also 'know' the difference between food/prey and surroundings barriers in some delightful way;

Bats fly arbitrarily with velocity v_i at location x_i with a frequency f_{min} , changeable wavelength γ and loudness A_0 to search for prey. They can repeatedly fine-tune the wavelength (or frequency) of their emitted pulses and fine-tune the rate of pulse emission, $r \in [0,1]$ depending on the closeness of their target;

Although the loudness can fluctuate in many ways, we assume that the loudness fluctuates from a large (positive) A_0 to a least constant value A_{\min} .

Following algorithm presents the standard Bat algorithm:

Bat Algorithm [7]:

Objective function $f(x)$, $x = (x_1, \dots, x_d)^T$
Initialize the bat population $x_i (i = 1, 2, \dots, n)$ and v_i
Define pulse frequency f_i at x_i
Initialize pulse rates r_i and the loudness A_i
while ($t < \text{Max number of iterations}$)
Generate new solutions by adjusting frequency, and updating velocities and locations/solutions [equations (2) to (4)]
if ($\text{rand} > r_i$)
Select a solution among the best solutions
Generate a local solution around the selected best solution
end if
Generate a new solution by flying randomly
if ($\text{rand} < A_i \ \& \ f(x_i) < f(x_*)$)
Accept the new solutions
Increase r_i and reduce A_i
end if
*Rank the bats and find the current best x_**
end while
Postprocess results and visualization

First of all, the starting position x_i , velocity v_i , and frequency f_i are initialized for every bat b_i . For each time step t , being T the limit of iterations, the movement of the virtual bats is specified by updating their velocity and position by means of equations 1, 2, and 3 as follows:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \quad (1)$$

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

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

Where $\beta \in [0, 1]$ is a random vector drawn from a uniform distribution, f_i denotes frequency of each bat, here x_* is the current global best solution (location) which is located after comparing all the solutions among all n bats, at each iteration. After the position updating of bats, a random number is generated, if the random number is larger than the pulse emission rate r_i , a new position will be generated around the current best solutions, and it can be represented by equation (4)

$$x_{\text{new}} = x_{\text{old}} + \varepsilon A^t \quad (4)$$

Where, $\varepsilon \in [-1, 1]$ is a random number, while A^t is the average loudness of all the bats at current iteration. Furthermore, the loudness A^i and the pulse emission rate r_i will be updated and a solution will be accepted if a random number is less than loudness A^i and $f(x_i) < f(x_*)$. A^i and r_i are updated by (5)

$$A_i^{t+1} = \alpha A_i^t, \quad r_i^{t+1} = r_i^0 [1 - \exp(-\gamma t)] \quad (5)$$

Where α, γ are constants? The algorithm iterates until the termination criteria is met.

III. MODIFICATION TO BAT ALGORITHM

To improve the enactment of novel BA, many means and strategies have been tried, which created variants of bat algorithm. This paper briefly discusses various modifications done to BA.

A fuzzy bat algorithm is proposed in [10] by introducing fuzzy logic into the bat algorithm. The modified algorithm was experienced on cluster analysis and found to be very effective. A binary bat algorithm for solving the well known economic load dispatch problem with the valve-point effect is proposed in [11]. Autohors concluded that their binary bat algorithm has many advantages. In the meantime, Nakamura et al. also presented a binary bat algorithm [12] that uses the sigmoid function. With the help of sigmoid function only binary allowed to new bat's position. They used this variant in feature selection problem. Furthermore, Sabba and Chikhi [13] also proposed a discrete binary variant of BA and tested it on multidimensional knapsack problem. With experimental results they concluded that this discrete binary BA outperformed the standard BA.

Zhang and Wang proposed a new bat algorithm with mutation [14] for image processing. They made two modifications to original BA. First, they used fixed frequency and loudness and second, they added a mutation operator to increase the diversity of the population. They tested it on image processing and found that the proposed algorithm produce good result than standard BA. The standard BA hybridized [15] with differential evolution techniques. This hybridization enhanced the local search capability of original BA.

Sabba et al. [16] improved the convergence speed of BA by embedding the opposition based numbering concept. They tested it against several benchmark functions. Simulation results showed that their approach increases the accuracy and convergence speed of BA. Xie et al. [17] also improved the low accuracy rate and slow convergence speed of BA. They

introduced levy flights trajectory which increases the diversity of population, so that the algorithm effectively jump out of local minima. They also used the differential operator to accelerate the convergence speed. The proposed algorithm was tested on typical benchmark functions and they concluded that their approach has superior approximation capabilities in high dimensional space. In [18], Afrabandpey et al. used chaotic sequence for parameter initialization of BA. They called it Chaotic BA (CBA). They studied the effect of different chaotic sequence on convergence behaviour of BA. Simulation result showed that CBA outperforms the BA. Meanwhile, Gandomi and Yang [19] also employed chaos in original BA. They developed four different chaotic BA variants and used 13 different chaotic maps to validate each variant. They concluded that their approach increase the global search mobility of BA.

Yilmaz et al. [20] improved the exploration mechanism of original BA. They changed the equation of loudness and pulse emission rate of bats. They tested this modified bat algorithm (MBA) on 15 different benchmark functions and concluded that MBA performs better than BA. Furthermore, Li and Zhou also enhanced the explorative mechanism of BA by introducing complex value encoding scheme into BA [21]. They update real and imaginary part of complex encoding separately which increases the diversity of population.

To tackle the high dimensionality problems, a variant of BA called bat algorithm with Gaussian walk was developed by Cai et al. [22]. They improved the local search capability by introducing the Gaussian walk instead of uniform random walk. They also changed the velocity update equation of BA which results in high population diversity. This approach expands the search dimensions. An interesting variant was developed by Zhou et al. [23]. They incorporated cloud model concept into BA and called it cloud model BA (CBA). Cloud model has excellent characteristics of representing uncertain knowledge [24]. They remodeled the echolocation model of BA by utilizing the transformation theory of cloud model. They studied that proposed algorithm had good performance on function optimizations. Another very interesting variant called compact bat algorithm (cBA) [25] was developed by Dao et al. for limited hardware resources environments. They replaced the design variable of solution search space of BA with a probabilistic representation of the population. Their study showed that this approach can be effectively used in limited memory case.

Fister et al. presented [26] a self-adaptive bat algorithm in which control parameters were self-adapted in the similar way like self-adaptive DE algorithm. They tested it on ten benchmark functions and found that proposed method can be

used in continuous optimization efficiently. Also, in [27] Fister et al. hybridized the self adaptive bat algorithm with different DE strategies. These techniques improved the local search capability of the proposed algorithm. Meanwhile, in [28] local and global search capability of BA was improved by using inertia weight modification, distribution of the population modification, and hybridization with invasive weed optimization algorithm [29]. Furthermore, for enhancing local and global search ability, Jun et al. developed a double sub-population levy flight BA (DLBA) [30]. They employed two subgroups namely external subgroup and internal subgroup. Global exploration improved by external subgroup and local exploitation was improved by the internal subgroup. They tested proposed algorithm on several test functions and concluded DLBA can outperform the BA. In addition, Meng et al. [31] introduced the bat's habitat selection and their self-adaptive compensation for Doppler Effect in echoes into the standard BA.

More recently, Wang et al. proposed [32] improved version of BA called it improved BA (IBA). They combine BA with DE in order to select the best solution in the bat population. They used this algorithm in three dimensional path planning problem and concluded that proposed approach can performed better than BA. On the other hand, Zhou et al. [33] successfully integrated the greedy randomized adaptive search procedure and path relinking into the standard BA. They used it in capacitated vehicle routing problem and found it very effective. For solving multi-model numerical problems, Cai et al. [34] proposed an improved version of BA. They improved the local search ability by using optimal forage strategy. They also introduced a random disturbance strategy to enhance the global search ability in multi-model environment. In addition, Zhu et al. [35] proposed a quantum behaved mean best position BA (QMBA) for improving the convergence speed of BA. In early stages of this algorithm, the position of each bat updated by current best solution and in later stages, bat's position depends upon the mean best position. Yammani et al. [36] proposed a hybrid multi objective shuffled BA (MOsh-BAT). They combine the features of shuffled frog leaping algorithm (SFLA) [37] and BA. The exploration capability of BA and exploitation method of SFLA was combined to form a new optimization algorithm.

IV. DISCUSSION AND CONCLUSION

This paper discusses the variety of research articles in the domain of BA. After the in-detail literature study, it is perceived that a large part of research was concentrated in the direction of modifying the BA to solve various kinds of problems. Even though BA has great potential, there are still

some vigorous issues that necessitate additional research such as parameter tuning and parameter controlling of BA. Spontaneous parameter tuning and controlling should be the topic of future research. BA does not use an operator similar to crossover in GA or DE, the sharing of fine information among solutions is not at requisite level. This causes the convergence performance of BA to be slow. This topic can also be searched and its convergence performance can be improved. In conclusion, BA remains a capable and attractive algorithm, which would be used widely by the researchers across various fields.

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