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Bat Algorithm: Literature Review and Applications

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Abstract

Yang created the bio-inspired Bat algorithm (BA) in 2010, and it has been shown to be very effective. Consequently, during the last three years, the literature has grown considerably. A relevant overview of the bat algorithm and its latest variations is given in this publication. Additionally, a variety of case studies and applications are evaluated and succinctly described here. There is also discussion of further research subjects.

Introduction

Modern optimization algorithms, which are usually based on swarm intelligence, are often influenced by nature. There are many various ways to be inspired, and as a result, there are many different kinds of algorithms. All of these algorithms, however, have a tendency to formulate the main updating equations using certain characteristics. For instance, Darwinian evolution features of biological systems served as inspiration for genetic algorithms, which include genetic operators including crossover, mutation, and selection of the fittest. Chromosomes or binary/real strings are used to represent solutions in genetic algorithms. However, the swarming behavior of fish and birds served as the basis for particle swarm optimization (PSO), a multi-agent system that may exhibit emergent swarm or group intelligence traits (Kennedy and Eberhart, 1995). The literature has several PSO variations and enhancements, as well as numerous novel metaheuristic algorithms (Cui, 2009; Yang, 2010; Yang and Deb, 2010; Yang et al., 2011; Yang et al., 2013).

While algorithms like PSO and genetic algorithms might be very helpful, they still have some limitations when it comes to multimodal optimization challenges. The firefly algorithm (FA), which was inspired by the flashing properties of tropical fireflies, is one significant advancement (Yang, 2008). The firefly method has the unexpected capacity to effectively tackle nonlinear, multimodal optimization problems thanks to the attraction behavior, light intensity coding, and distance dependency. Additionally, the brooding behavior of some cuckoo species (Yang and Deb, 2009; Gandomi et al., 2013) provided the basis for cuckoo search (CS), which was integrated with levy flights. Markovian probability theory may be used to demonstrate the CS algorithm's excellent convergence behavior, which makes it efficient. Other approaches, like the eagle technique, are also very successful (Yang and Deb, 2010; Gandomi et al, 2012).

The bat algorithm (BA) was developed as a novel feature based on the echolocation characteristics of microbats (Yang, 2010). BA employs automatic zooming to attempt to balance exploration and exploitation during the search process while also using a frequency-tuning technique to increase the diversity of the solutions in the population.

imitating the fluctuations in bat loudness and pulse emission rates during prey hunting. Consequently, it turns out to be very effective with a normal fast start. There is undoubtedly space for development. Thus, the goal of this research is to examine the most recent advancements in the bat algorithm. The structure of the paper is as follows: The typical formulation of the bat algorithm and the fundamental behavior of echolocation are introduced in Section 2. The variations of BA are briefly described in Section 3, and the many uses of the bat algorithm and its variations are highlighted in Section 4. Section 5 concludes with a few talks and research ideas.

The Standard Bat Algorithm

The echolocation or bio-sonar features of microbats served as the foundation for the conventional bat algorithm. Let's provide a quick overview of the echolocation before delving into the algorithm's specifics.

Echolocation of Microbats

There are about 1000 different species of bats (Colin, 2000). Their sizes can vary widely, ranging from the tiny bumblebee bat of about 1.5 to 2 grams to the giant bats with wingspan of about 2 m and may weight up to about 1 kg. Most bats uses echolocation to a certain degree; among all the species, microbats use echolocation extensively, while megabats do not.

Microbats typically use a type of sonar, called, echolocation, to detect prey, avoid obstacles, and locate their roosting crevices in the dark. They can emit a very loud sound pulse and listen for the echo that bounces back from the surrounding objects (Richardson, 2008). Their pulses vary in properties and can be correlated with their hunting strategies, depending on the species. Most bats use short, frequency-modulated signals to sweep through about an octave, and each pulse lasts a few thousandths of a second (up to about 8 to 10 ms) in the frequency range of 25kHz to 150 kHz. Typically, microbats can emit about 10 to 20 such sound bursts every second, and the rate of pulse emission can be sped up to about 200 pulses per second when homing on their prey. Since the speed of sound in air is about $v = 340$ m/s, the wavelength λ of the ultrasonic sound bursts with a constant frequency f is given by $\lambda = v/f$, which is in the range of 2mm to 14mm for the typical frequency range from 25kHz to 150 kHz. Interestingly, these wavelengths are in the same order of their prey sizes.

Though in reality microbats can also use time delay between their ears and loudness variations to sense three-dimensional surroundings, we are mainly interested in some features of the echolocation so that we can some link them with the objective function of an optimization problem, which makes it possible to formulate a smart, bat algorithm.

Bat Algorithm

Based on the above description and characteristics of bat echolocation, Xin-She Yang (2010) developed the bat algorithm with the following three idealised rules:

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

Bats fly randomly with velocity v_i at position x_i with a frequency $f_{\min}$, varying wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r \in [0, 1]$, depending on the proximity of their target;

Although the loudness can vary in many ways, we assume that the loudness varies from a large (positive) A_0 to a minimum constant value $A_{\min}$.

or simplicity, we do not use ray tracing in this algorithm, though it can form an interesting feature for further extension. In general, ray tracing can be computational extensive, but it can be a very useful feature for computational geometry and other applications. Furthermore, a given frequency is intrinsically linked to a wavelength. For example, a frequency range of [20kHz, 500kHz] corresponds to a range of wavelengths from 0.7mm to 17mm in the air. Therefore, we can describe the change either in terms of frequency f or wavelength λ to suit different applications, depending on the ease of implementation and other factors.

Bat Motion

Each bat is associated with a velocity v_i^t and a location x_i^t, at iteration t, in a d-dimensional search or solution space. Among all the bats, there exists a current best solution x_*. Therefore, the above three rules can be translated into the updating equations for x_i^t and velocities v_i^t:

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

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

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

where $\beta \in [0, 1]$ is a random vector drawn from a uniform distribution.

As mentioned earlier, we can either use wavelengths or frequencies for implementation, we will use $f_{\min} = 0$ and $f_{\max} = O(1)$, depending on the domain size of the problem of interest. Initially, each bat is randomly assigned a frequency which is drawn uniformly from [$f_{\min}$,

$f_{\max}$]. For this reason, bat algorithm can be considered as a frequency-tuning algorithm to provide a balanced combination of exploration and ex- ploitation. The loudness and pulse emission rates essentially provide a mechanism for automatic control and auto zooming into the region with promising solutions.

Variations of Loudness and Pulse Rates

In order to provide an effective mechanism to control the exploration and exploitation and switch to exploitation stage when necessary, we have to vary the loudness A_i and the rate r_i of pulse emission during the iterations. Since the loudness usually decreases once a bat has found its prey, while the rate of pulse emission increases, the loudness can be chosen as any value of convenience, between $A_{\min}$ and $A_{\max}$, assuming $A_{\min} = 0$ means that a bat has just found the prey and temporarily stop emitting any sound. With these assumptions, we have

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

where α and γ are constants. In essence, here α is similar to the cooling factor of a cooling schedule in simulated annealing. For any $0 < \alpha < 1$ and $\gamma > 0$, we have

$$A_i^t \to 0, \quad r_i^t \to r_i^0, \quad \text{as } t \to \infty. \qquad (5)$$

In the simplest case, we can use $\alpha = \gamma$, and we have used $\alpha = \gamma = 0.9$ to 0.98 in our simulations.

Variants of Bat Algorithm

The standard bat algorithm has many advantages, and one of the key advantages is that it can provide very quick convergence at a very initial stage by switching from exploration to exploitation. This makes it an efficient algorithm for applications such as classifications and others when a quick solution is needed. However, if we allow the algorithm to switch to exploitation stage too quickly by varying A and r too quickly, it may lead to stagnation after some initial stage. In order to improve the performance, many methods and strategies have been attempted to increase the diversity of the solution and thus to enhance the performance, which produced a few good variants of bat algorithm.

From a quick literature survey, we found the following bat algorithm variants:

Fuzzy Logic Bat Algorithm (FLBA): Khan et al. (2011) presented a variant by introducing fuzzy logic into the bat algorithm, they called their variant fuzzy bat algorithm.

Multiobjective bat algorithm (MOBA): Yang (2011) extended BA to deal with multiobjective optimization, which has demonstrated its effectiveness for solving a few design benchmarks in engineering.

K-Means Bat Algorithm (KMBA): Komarasamy and Wahi (2012) presented a combination of K-means and bat algorithm (KMBA) for efficient clustering.

Chaotic Bat Algorithm (CBA): Lin et al. (2012) presented a chaotic bat algorithm using L´evy flights and chaotic maps to carry out parameter estimation in dynamic biological systems.

Binary bat algorithm (BBA): Nakamura et al. (2012) developed a discrete version of bat algorithm to solve classifications and feature selection problems.

Differential Operator and L´evy flights Bat Algorithm (DLBA): Xie et al. (2013) presented a variant of bat algorithm using differential operator and L´evy flights to solve function optimization problems.

Improved bat algorithm (IBA): Jamil et al. (2013) extended the bat algorithm with a good combination of L´evy flights and subtle variations of loudness and pulse emission rates. They tested the IBA versus over 70 different test functions and proved to be very efficient.

There are other improvements and variants of bat algorithm. For example, Zhang and Wang (2012) used mutation to enhance the diversity of solutions and then used for image matching. In addition, Wang and Guo (2013) hybridized bat algorithm with harmony search and have produced a hybrid bat algorithm for numerical optimization of function benchmarks.

On the other hand, Fister Jr et al. (2013) developed a hybrid bat algorithm using differential evolution as a local search part of bat algorithm, while Fister et al. (2013) incorporate quaternions into bat algorithm and presented a quaternion bat algorithm (QBA) for computational geometry and large-scale optimization problems with exten- sive rotations. It can

be expect that more variants are still under active research.

Applications of Bat Algorithm

The standard bat algorithm and its many variants mean that the applications are also very diverse. In fact, since the original bat algorithm has been developed (Yang, 2010), Bat algorithms have been applied in almost every area of optimization, classifications, image processing, feature selection, scheduling, data mining and others. In the rest of the paper, we will briefly highlight some of the applications (Yang, 2010;Parpinelli and Lopes, 2011; Yang et al., 2012a; Yang, 2012; Yang, 2013; Gandomi et al., 2013).

Continuous Optimization

Among the first set of applications of bat algorithm, continuous optimization in the context of engineering design optimization has been extensively studied, which demon- strated that BA can deal with highly nonlinear problem efficiently and can find the optimal solutions accurately (Yang, 2010; Yang and Gandomi, 2012; Yang, 2012; Yang et al., 2012a). Case studies include pressure vessel design, car side design, spring and beam design, truss systems, tower and tall building design and others. Tsai et al. (2011) solved numerical optimization problems using bat algorithm.

In addition, Bora et al. (2012) optimized the brushless DC wheel motors using bat algorithm with superior results. BA can also handle multiobjective problems effectively (Yang, 2011).

Combinatorial Optimization and Scheduling

From computational complexity point of view, continuous optimization problems can be considered as easy, though it may be still very challenging to solve. However, com- binatorial problems can be really hard, often non-deterministic polynomial time hard (NP-hard). Ramesh et al. (2013) presented a detailed study of combined economic load and emission dispatch problems using bat algorithm. They compared bat algo- rithm with ant colony algorithm (ABC), hybrid genetic algorithm and other methods, and they concluded that bat algorithm is easy to implement and much superior to the algorithms in terms of accuracy and efficiency.

Musikapun and Pongcharoen (2012) solved multi-stage, multi-machine, multi-product scheduling problems using bat algorithm, and they solved a class of non-deterministic polynomial time (NP) hard problems with a detailed parametric study. They also im- plied that that the performance can be further improved by about 8.4% using optimal set of parameters.

Inverse Problems and Parameter Estimation

Yang et al. (2012b) use the bat algorithm to study topological shape optimization in microelectronic applications so that materials of different thermal properties can be placed in such a way that the heat transfer is most efficient under stringent constraints. It can also be applied to carry out parameter estimation as an inverse problem. If an inverse problem can be properly formulated, then bat algorithm can provide better results than least-squares methods and regularization methods.

Lin et al. (2012) presented a chaotic L´evy flight bat algorithm to estimate parameters in nonlinear dynamic biological systems, which proved the effectiveness of the proposed algorithm.

Classifications, Clustering and Data Mining

Komarasamy and Wahi (2012) studied K-means clustering using bat algorithm and they concluded that the combination of both K-means and BA can achieve higher efficiency and thus performs better than other algorithms.

Khan et al. (2011) presented a study of a clustering problem for office workplaces using a fuzzy bat algorithm. Khan and Sahari (2012a) also presented a comparison study of bat algorithm with PSO, GA, and other algorithms in the context for e-learning, and thus suggested that bat algorithm has clearly some advantages over other algorithms. Then, they (Khan and Sahari,

2012b) also presented a study of clustering problems using bat algorithm and its extension as a bi-sonar optimization variant with good results.
On the other hand, Mishra et al. (2012) used bat algorithm to classify microarray data, while Natarajan et al. (2012) presented a comparison study of cuckoo search and bat algorithm for Bloom filter optimization. Damodaram and Valarmathi (2012) studied phishing website detection using modified bat algorithm and achieved very good results.
Marichelvam and Prabaharan (2012) used bat algorithm to study hybrid flow shop scheduling problems so as to minimize the makespan and mean flow time. Their results suggested that BA is an efficient approach for solving hybrid flow shop scheduling prob- lems. Faritha Banu and Chandrasekar (2013) used a modified bat algorithm to record deduplication as an optimization approach and data compression technique. Their study suggest that the modified bat algorithm can perform better than genetic programming.

Image Processing
Abdel-Rahman et al. (2012) presented a study for full body human pose estimation using bat algorithm, and they concluded that BA performs better than particle swarm optimization (PSO), particle filter (PF) and annealed particle filter (APF).
Du and Liu (2012) presented a variant of bat algorithm with mutation for image matching, and they indicated that their bat-based model is more effective and feasi- ble in imagine matching than other models such as differential evolution and genetic algorithms.

Fuzzy Logic and Other Applications
Reddy and Manoj (2012) presented a study of optimal capacitor placement for loss reduction in distribution systems using bat algorithm. It combines with fuzzy logic to find optimal capacitor sizes so as to minimize the losses. Their results suggested that the real power loss can be reduced significantly.
Furthermore, Lemma et al. (2011) used fuzzy systems and bat algorithm for exergy modelling, and later Tamiru and Hashim (2013) applied bat algorithm to study fuzzy systems and to model exergy changes in a gas turbine.
At the time of writing when we searched the Google scholar and other databases, we found other papers on bat algorithm that were either just accepted or conference presentations. However, there is not enough detail to be included in this review. In fact, as the literature is expanding, more and more papers on bat algorithm are emerging, a further timely review will be needed within the next two years.

Discussions and Conclusions
The bat algorithm, like many other metaheuristic algorithms, has the benefit of being straightforward and adaptable. As seen in the overview above, BA is a straightforward algorithm that may be used to tackle a variety of issues.

Why Bat Algorithm is Efficient
Why the bat algorithm is so effective is a logical issue. The success of bat-based algorithms may be attributed to several factors. The following three important points/features may be summed up by analyzing the main characteristics and updating equations:
• Frequency tuning: BA employs frequency tuning and echolocation to address issues. Frequency fluctuations are employed, even though echolocation does not exactly replicate the genuine function in reality. This skill can provide some functionality that may be comparable to the essential component used in harmony search and particle swarm optimization. As a result, BA has the benefits of other algorithms based on swarm intelligence.•Automatic zooming: Compared to other metaheuristic algorithms, BA offers a clear advantage. In other words, BA may automatically zoom in on an area where interesting answers have been discovered. Alongside this zooming is the

automatic transition from exploratory to extensive local exploitation. As a result, as compared to other algorithms, BA has a rapid convergence rate, at least in the early stages of the iterations.
•Parameter control: By using certain pre-tuned algorithm-dependent parameters, several metaheuristic algorithms used fixed parameters. BA, on the other hand, employs parameter control, which allows the values of parameters (A and r) to change as the iterations go on. This makes it possible to seamlessly transition from exploration to exploitation as the ideal answer gets closer. This provides BA an additional edge over other metaheuristic algorithms.
Furthermore, preliminary theoretical research by Huang et al. (2013) indicated that BA may successfully handle large-scale problems and has assured global convergence features under the correct conditions.

Further Research Topics
Nonetheless, there are still a few significant problems that need more investigation. These three main concerns are acceleration of convergence, parameter control, and parameter tweaking.
First, for any metaheuristic algorithm to function properly, parameter tweaking is crucial. Almost always, an algorithm's performance is heavily influenced by its parameters. Detailed parametric studies must be conducted in order to determine the optimal parameter settings. The possibility of automatically adjusting an algorithm's parameters to get the best performance for a particular collection of challenges is yet unknown. This ought to be a significant area for more study.
Second, there is a significant problem with parameter control related to parameter tuning. Many algorithms have fixed parameter sets that remain constant throughout the rounds. During the iterative search process, changing the values of algorithm-dependent parameters may be beneficial and sometimes required. Another, more complex optimization challenge that requires further research is how to change or regulate these parameters. Although we have shown the fundamental parameter management technique for the bat algorithm, there is yet opportunity for improvement. What is the optimal control method to transition from exploration to exploitation at the appropriate moment is an outstanding subject.
Lastly, even if the bat algorithm and other algorithms are effective, their performance may still be further improved. Nevertheless, the subject of how to accelerate an algorithm's convergence remains very difficult. It is anticipated that this work will stimulate more research in the near future. Future studies should concentrate on the theoretical comprehension of large-scale issues in practical applications and metaheuristic algorithms.

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