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Algorithms Artificial Bee Colony Optimization with No Random Selection

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Abstract

Artificial Bee Colony (ABC) is conceivably the most actually portrayed figuring by DervisKaraboga in 2005, enlivened by the wise lead of honey bees. It is basically pretty much as fundamental as Particle Swarm Optimization (PSO) and Differential Evolution (DE) figuring, and uses simply ordinary control limits, for instance, settlement size and most limit cycle number. ABC as a progression mechanical assembly, gives a general population based request strategy in which individuals called sustenance positions are changed by the phony bumble bees with time and the bumble bee's point is to discover the spots of food sources with high nectar aggregate ultimately the one with the most critical nectar. In ABC system, counterfeit bumble bees fly around in a multidimensional request space and a couple (used and bystander bumble bees) pick food sources depending upon the experience of themselves and their home mates, and change their positions. A couple (scouts) flies and pick the food sources indiscriminately without using experience. If the nectar proportion of another source is higher than that of the previous one in their memory, they hold the new position and neglect to recollect the previous one. In this way, ABC system merges close by pursuit procedures, done by used and bystander bumble bees, with overall chase methods, managed by observers and scouts, trying to change examination and abuse measure.

Keywords: — Machine Learning, Artificial Intelligence, Swarm Intelligence, Artificial Bee Colony Optimization.

1 INTRODUCTION

SWARMintelligence (SI) is basically the total direct of decentralized, facilitated systems, customary or counterfeit. The thought is used in work on man-made thinking. SI structures involve conventionally of a general population of essential trained professionals or boids interfacing locally with one another and with their present condition.The experts notice incredibly fundamental rules, and regardless of the way that there is no concentrated control structure coordinating how particular experts should continue, neighborhood, and in a restricted way discretionary, correspondences between such experts lead to the ascent of "quick" overall direct, dark to the individual trained professionals. Occasions of huge number understanding in ordinary structures consolidate underground creepy crawly territories, bird running, hawks pursuing, animal gathering, bacterial turn of events, fish mentoring and microbial information. The utilization of huge number principles to robots is called swarm mechanical innovation while swarm information implies the more extensive plan of computations. Large number assumption has been used concerning expecting issues. Comparative ways to deal with those proposed for swarm advanced mechanics are considered for hereditarily adjusted living beings in engineered aggregate knowledge. Swarm Intelligence is simply the aggregate conduct of decentralized, coordinated frameworks. An ordinary multitude insight framework comprises of a populace of straightforward specialists which can convey (either straightforwardly or in a roundabout way) locally with one another by following up on their neighborhood climate.
Machine Learning is a mechanism that concerned with writing a computer program that automatically improves with experience. It is a very young scientific discipline whose birth can be placed in the mid-seventies. A student can exploit models (information) to catch attributes of interest of their obscure basic likelihood conveyance. Information can be viewed as models that delineate relations between noticed factors. A significant focal point of AI research is to naturally figure out how to perceive complex examples and settle on smart choices dependent on information; the trouble lies in the way that the arrangement of all potential practices given all potential sources of info is too enormous to possibly be covered by the arrangement of noticed models

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(preparing information). Consequently the student should sum up from the given models, in order to have the option to create a helpful yield in new cases. Artificial intelligence is a closely related field, as are probability theory and statistics, data mining, pattern recognition, and theoretical computer science. There were many successful applications of machine learning exists today, including systems that analyze past sales data to predict customer behavior, recognize faces or spoken speech, optimize robot behavior so that a task can be completed using minimum resources, and extract knowledge from bioinformatics data.

The fake honey bee province enhancement (ABC) is a populace based calculation for work improvement that is roused by the scrounging conduct of honey bees. The populace comprises of two kinds of fake honey bees: utilized honey bees (EBs) which scout for new great arrangement in the hunt space and spectator honey bees (OBs) that inquiry in the neighborhood of arrangements found by the EBs. Artificial Bee Colony (ABC) is conceivably the most actually portrayed figuring by DervisKaraboga in 2005, enlivened by the wise lead of honey bees. It is basically pretty much as fundamental as Particle Swarm Optimization (PSO) and Differential Evolution (DE) figuring, and uses simply ordinary control limits, for instance, settlement size and most limit cycle number. ABC as a progression mechanical assembly, gives a general population-based request strategy in which individuals called sustenance positions are changed by the phony bumble bees with time and the bumble bee's point is to discover the spots of food sources with high nectar aggregate ultimately the one with the most critical nectar. In ABC system, counterfeit bumble bees fly around in a multidimensional request space and a couple (used and bystander bumble bees) pick food sources depending upon the experience of themselves and their home mates, and change their positions. A couple (scouts) flies and pick the food sources indiscriminately without using experience. If the nectar proportion of another source is higher than that of the previous one in their memory, they hold the new position and neglect to recollect the previous one. In this way, ABC system merges close by pursuit procedures, done by used and bystander bumble bees, with overall chase methods, managed by observers and scouts, trying to change examination and abuse measure.

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2 APPLICATIONS OF ARTIFICIAL BEE COLONY ALGORITHM

Artificial Bee Colony is been one of the most impressive algorithms for optimization operations for various fields. ABC is well suited for general assignment problem, cluster analysis, constrained problem optimization, structural optimization, and advisory system. It has also been applied to software engineering for software testing and parameter estimation in software reliability growth models. ABC also plays an important role in medical, as used in MR brain image classification, face pose estimation, bioinformatics etc. The successful applications of ABC and its rapid growth suggest that its impact will be felt increasingly in coming years. It persuades the use of ABC and its tools into different advanced applications. It is hoped that this paper will benefit computer scientist who are keen to contribute their works to the field of artificial bee colony

3 LITERATURE SURVEY

Karaboga and Basturk in [1] extended the ABC algorithm to handle constrained optimization problems. A set of 13 benchmark optimization problems was examined, and the results were compared with Differential Evolution (DE) and PSO algorithms. The same authors of [1] in [2] examined the performance of the ABC algorithm in five benchmark optimization functions, with the dimension of each function varying from 10 to 30. The results outperformed other metaheuristic and hybrid algorithms such as PSO, GA and hybrid Evolution Algorithm (EA) and PSO (PS-EA).

The authors of [3] performed an analysis of the control parameters of ABC algorithm with a set of 5 benchmark optimization functions and compared the results with those of PSO, EA and DE algorithms. Furthermore, three of the examined functions have 50 parameters to be optimized.

A large set of over 50 benchmark optimization functions was solved by the ABC algorithm in [4]. The results were compared with those obtained using other competing methods in three experiments. Throughout this large comparative analysis, statistical measurements proved the superiority of the ABC algorithm compared to most other well-known metaheuristic optimization algorithms.

The authors of [5] utilized the ABC algorithm in solving large-scale optimization problems. A set of 9 benchmark (unconstrained) optimization functions and engineering (constrained) optimization problems was adopted to illustrate the performance of the ABC method. The superiority of the ABC algorithm in handling both constrained and unconstrained optimization problems was demonstrated.

The Sudoku puzzle was solved in [6] via the ABC algorithm. The puzzle is considered a logic-based problem with three constraints [6]. The authors considered three types (easy, medium and hard) of Sudoku puzzles to demonstrate the efficiency of their proposed method. The offered method outperformed other GA-based Sudoku solutions.

The protein-folding problem is a challenging biochemistry energy minimization task which can be solved experimentally or computationally. Experimental results are accurate but are expensive and time consuming. Due to these limitations, scientists solved this problem as an optimization problem. The authors of [7] utilized the ABC algorithm to identify the protein structure, and compared the results to other techniques.

In [8] the ABC algorithm was put in to unravel integer programming troubles. Several test problems were considered, and the results were compared with those obtained utilizing various techniques. The integer characteristics of the problems were basically handled by rounding off the calculated solutions to the closest feasible values.

Akay and Karaboga, in [9] analyzed the effect of parameters-tuning on the performance of the ABC algorithms. A set of 9 benchmark optimization functions were adopted, and the results were compared with those of PSO and DE techniques. The proportions of the trialedconsequences were 10, 100 and 1000 variables.

The authors of [10] utilized the ABC algorithm to train feed-forward neural networks. Three tests were considered: the Exclusive-OR, 3-Bit Parity and 4-Bit Encoder-Decoder problems. The solutions obtained by the proposed algorithm were compared with those attained using the GA and Back Propagation (BP) techniques.

A modified version of the ABC algorithm was proposed in [11]. The main difference in this paper was that once a solution i did not improve for a specified number of trials, the whole algorithm was terminated. Subsequently, the employed bees became scouts and explored new solutions randomly. The neighboring searches were always dominated by the best solution associated with employed and onlooker bees. The authors considered 10 benchmark optimization functions and 10 optimized parameters.

The authors of [12] used the ABC algorithm routine to improve the Quantum EA (QEA) algorithm. The main advantage of the suggested hybrid technique was to overcome some of the limitations of a QEA. In other words, the crossover and mutation processes were directed by the ABC strategy.

Three modified selection mechanisms of the ABC algorithm were offered in [13] and suggested to replace the existing probability (directly proportional) selection process of the original ABC algorithm. The main reason was to increase the diversity of the population. The performance of those strategies compared with the original one via multiple benchmark optimization functions.

An adapted ABC algorithm was proposed by Liu and Cai in [14]. The suggested ABC programming (ABCP) approach increased the number of onlooker bees. In addition, it included the Layer Noise Crossover (LNX) operation for the neighboring search after dividing the solutions into three (best, worst and those in-between) subsets. The aim of such modification was to enhance and accelerate the algorithm's performance. A set of 15 benchmark optimization functions was considered for evaluating the offered method. Results of the ABC and Self Adapted DE (SADE) algorithms were compared with those obtained using the proposed method.

Analysis of the impact of the ABC's parameters was presented in [15]. In addition, the authors offered a modified ABC algorithm that altered the neighbouring search procedures used in the original version. They also substituted the probability equation with the Euclidean distance formula. Moreover, different versions of PSO, DE, ABC and ACO techniques were adopted for comparison.

Instead of the initial random solutions used in the original ABC algorithm, the author of [16] proposed three versions of the ABC algorithm based on Chaotic mapping sequences. The performance was assessed via three benchmark optimization functions, and compared with the original ABC method. Various chaotic mapping categories were also employed to prove the proposed versions' competence.

The authors of [17] adapted the ABC algorithm (based on Chaos theory) to solve the Uninhabited Combat Aerial Vehicle (UCAV) problem, which was to obtain the optimal path of an aircraft (with predetermined start and target points) in such a way to avoid the threats distributed on the search-space. The flight's path was divided into segments using vertical lines. An experiment with various segments was used to evaluate the method's performance. It was shown that once the path's segments increased, the proposed algorithm attained improved solutions.

The ABC algorithm has been used in data clustering and image analysis applications. Ref. [18] detected the image of an aircraft at low-altitude. In other words, the Edge Potential Function (EPF) was deployed in the optimization process by maximizing the similarities between the target and actual images. The authors highlighted additional insights of the convergence and complexity of the ABC algorithm through probability theories. Four experiments were conducted using the ABC method in [19] to find the pattern of an object with gray and color images. The Euclidean distance formula was used in [20] to solve the clustering problem via the ABC algorithm. A variety of commonly used statistical methods was adopted for comparison, as well. A combination of the ABC algorithm and Greedy Randomized Adaptive Search Procedure (GRASP) method was proposed in [21]. The offered hybrid technique solved the clustering problem in two stages – The first dedicated for the ABC algorithm by determining the feature-based selection, and the second by the clustering task assigned for the GRASP method. The authors also utilized the sigmoid function in order to transfer the (continuous) possible solutions into discrete types. Ref. [22] utilized the ABC algorithm to minimize the Euclidean distance between an object and its associated cluster center.

Computer science applications have used the ABC algorithm in [23] and [24]. The Leaf-Constrained Minimum Spanning Treecrisis has been answered in [23]. The objective function was to find a spanning tree with the minimum total weight. Furthermore, an alternative (scout-bees) exploration routine has been included in the offered algorithm to avoid premature or duplicate solutions. The authors of [24] deployed the ABC algorithm in performing the software testing problem. The ACO method was used for comparison purposes through different types of problems. The objective function was to minimize the time in a path convergence.

3 PROPOSED WORK

Implemented algorithm follows the same route for the ABC algorithm. The model defines three principal components which are enunciated as follows.

Food Source. The value of a food source depends on many different factors, as its proximity to the beehive, wealth or the concentration of the energy, and the facility of extraction of this energy.

Employed Bees or Workers. They are associated with a current food source, or in exploitation, they take with them information about this source, especially the distance, location, and profitability, to share this with a certain probability with other companions.

Unemployed or Exploratory Bees. There are two types: (i) scouts: they are the ones in charge of searching in the environment that surrounds the beehive for new sources of food. (ii) onlookers (curious or in wait): they look for a food source across the information shared by the employees or by other explorers in the nest.

The algorithm has been updated over the partner selection; the base algorithm equation suggests changing only the randomly selected value in accordance with the partner value selected from the position of different particle. Also, the base algorithm says to randomly update or add the vector value and follow the boundary conditions whereas in this dissertation the values got updated using the equation stated below:

$$v_{ij} = x_{ij} + \emptyset_{ij}\,(x_{ij} - x_{kj})$$

Where k represents the random particle amongst the swarm size and j represents the decision variable count, i represents the current particle value for which the solution has been generated. Also I remains the constant but the value of j varies from 1 to up to the last decision variable count, for instance if the decision variable count is 6 the value of j will vary from 1 to 6, and the new solution will be generated for all the decision variables and none will be spared, this helps in minimizing the effect of random values and generate the new solution which are now more inspired by the existing solution and more relatable in terms of fitness and distances between the two particles.

3 RESULTS

The code has been tested extensively and it yields graphical representation of each iteration for each simulation.

Table 1: Input Values for 3 Simulation Configurations

S.No	Swarm Size	Lower Bound	Upper Bound	Decision Variables	Iteration Count
1	10	0	10	5	50
2	20	0	100	10	50
3	50	0	1000	15	50
4	1000	0	1000	20	50

The simulations have been conducted over the parameters stated in the above table. The results shows that the algorithm implemented in Big O notation algorithm where the simulation time increases with increase in the size of the datasets.The simulation with swarm size of 10, decision variable count of 5 and the limits to be [0, 10] for 50 iterations took 4.22 seconds along with the graphical pause.The simulation with swarm size of 20, decision variable count of 10 and the limits to be [0, 100] for 50 iterations took 4.11 seconds along with the graphical pause.The simulation with swarm size of 50, decision variable count of 15 and the limits to be [0, 1000] for 50 iterations also took 4.11 seconds along with the graphical pause.The simulation with swarm size of 1000, decision variable count of 20 and the limits to be [0, 1000] for 50 iterations took 12.72 seconds along with the graphical pause.

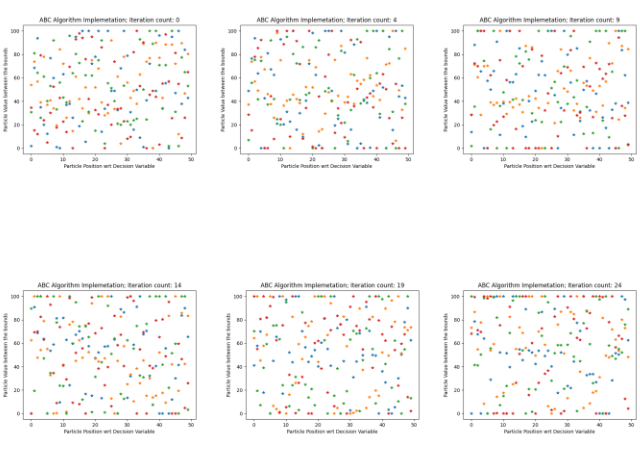

Figure 1: Graphical representation of the simulation of the ABC algorithm.

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