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A Comparative Study on Artificial Bee Colony with Modified ABC Algorithm

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Abstract: Artificial bee colony optimization algorithm is one of the popular swarm intelligence technique anticipated by D. Karaboga in year 2005. In this work, ABC is used to extract the optimal knowledge extraction from the knowledge discovery in database (KDD) dataset. The results produced by ABC algorithm are compared with the results obtained by the combination of ABC and Cuckoo Search. The performance results of the combined ABC and Cuckoo Search is better than ABC population-based algorithm. These algorithms are very simple to implement so we combined the ABC optimization algorithm with the CS algorithm to solve very complex problems.

Key words: Knowledge Data Discovery · Swarm Intelligence · Nature Inspired Algorithm · Artificial Bee Colony and Cuckoo Search

INTRODUCTION

Swarm Intelligence based algorithm are very popular nowadays while solving complex problem in field of engineering, management and science. These algorithms are inspired by some natural phenomenon and called Nature Inspired Algorithms (NIAs).Karthik Sindhya [1] and Brownlee, Clever [2] The NIAs mimics the intelligent behavior of social insects like bees, ants, termites, fish, birds, etc. Swarm Intelligence getting popularity now days and become a rising and fascinating area. It depends on the cooperative behavior of societal living thing. Societal individual makes use of their skill of societal wisdom to crack multifaceted everyday jobs. The main power of swarm based optimization strategy is multiple interactions in societal colonies. Swarm intelligence strategies have the potential to solve complex factual world optimization problems as the preceding study have exposed. Recently D. Karaboga [3] proposed a very simple and easy to implement strategy motivated by extraordinary food foraging behavior of honey bee insects and named it as artificial bee colony algorithm. Resembling to other population based optimization algorithms, this algorithm also has a population of budding solutions. Food source for a honey bee represent one possible solution. Fitness of a particular food source, computes its quality that represents the amount of nectar in a food source. Performance of the ABC algorithm depends on the steadiness between searching of local search space and utilization of best feasible outcomes. Every so often it is practical that the ABC prevents proceeding headed for the global most favourable despite the fact that the local optimum not achieved.

The ABC was used for data clustering on benchmark problems and its performance was compared to a particle swarm optimization algorithm Thirteen typical test data sets from UCI Machine Learning Repository demonstrated techniques results. The simulation indicated that ABC algorithm was efficient for multivariate data clustering. ABC can be used to solve high dimensionality engineering problems. Since the ABC algorithm is simple in concept, easy to implement and has fewer control parameters, it has been widely used in many optimization applications such as protein tertiary structures, digital IIR filters, artificial neural networks and others.

The first introduction of Cuckoo Search (CS) by Xin-SheYang and SuashDeb [4], this algorithm has exploded. Cuckoo search, which drew its inspiration from the brooding parasitism of cuckoo species in Nature, were firstly proposed as a tool for numerical function optimization and continuous problems. Researchers tested this algorithm on some well-known benchmark functions and compared with PSO and GA and it was found that cuckoo search achievedbetter results than the results by PSO and GA. Since then, the original

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developers of this algorithm and many researchers have also applied this algorithm to engineering optimization, where Cuckoo search also showed promising results. Nowadays cuckoo search has been applied in almost every area and domain of function optimization, engineering optimization, image processing, scheduling, planning, feature selection, forecasting and real-world applications.

Related Work: Sandeep Kumar [5] This paper introduces a local search strategy that enhances exploration competence of ABC and avoids the problem of stagnation. The proposed strategy introduces two new local search phases in original ABC. One just after onlooker bee phase and one after scout bee phase. The newly introduced phases are inspired by modified Golden Section Search (GSS) strategy.X. Li and Guangfei Yang. [6] "Artificial bee colony algorithm with memory." In this paper, a new ABC variant named ABC with memory algorithm (ABCM) is described, which imitates a memory mechanism to the artificial bees to memorize their previous successful experiences of foraging behavior. The memory mechanism is applied to guide the further foraging of the artificial bees.S. Kumar, V. K. Sharma and R. Kumari. [7] "Improved Onlooker Bee Phase in Artificial Bee Colony Algorithm." This paper improve onlooker bee phase with help of a local search strategy inspired by memetic algorithm to balance the diversity and convergence capabilityof the ABC.

Ozturk, Celal, Emrah Hancer and Dervis Karaboga [8] "A novel binary artificial bee colony algorithm based on genetic operators." This study proposes a novel binary version of the artificial bee colony algorithm based on genetic operators (GB-ABC) such as crossover and swap to solve binary optimization problems. Integrated to the neighbourhood searching mechanism of the basic ABC algorithm, the modification comprises four stages: (1) In neighbourhood of a (current) food source, randomly select two food sources from population and generate a solution including zeros (Zero) outside the population; (2) apply two-point crossover operator between the current, two neighbourhood, global best and Zero food sources to create children food sources; (3) apply swap operator to the children food sources to generate grandchildren food sources; and (4) select the best food source as a neighbourhood food source of the current solution among the children and grandchildren food sources. D. Karaboga and B. Akay [9]. In this work, ABC is used for optimizing a large set of numerical test functions and the results produced by ABC algorithm are compared with the results obtained by genetic algorithm, particle swarm optimization algorithm, differential evolution algorithm and evolution strategies. Results show that the performance of the ABC is better than or similar to those of other population-based algorithms with the advantage of employing fewer control parameters.

Yurtkuran, Alkın and Erdal Emel [10]. In this work, instead of using a single search operator to generate neighbour solutions, random selection from an operator pool is employed. Moreover, novel crossover operators are presented and employed with several parent sets with different characteristics to enhance both exploration and exploitation behaviour of the proposed algorithm.C. Caraveo, Fevrier Valdez and Oscar Castillo [11]. In this paper we are presenting a modification of a bio-inspired algorithm based on the bee behavior (BCO, bee colony optimization) for optimizing fuzzy controllers. BCO is a metaheuristic technique inspired by the behavior presented by bees in nature, which can be used for solving optimization problems. JC Bansal, H Sharma and SS Jadon12] This paper presents a review on ABC developments, applications, comparative performance and future research perspectives.

Artificial Bee Colony Algorithm: The ABC strategy is population based stochastic search strategy in the area of nature-inspired optimization strategies. The position of swarm updates in ABC by two different activities: first one is a process of adaptation, which empowers exploring the diverse search space and the second one is a process of selection, which ensures the exploitation of the earlier experience. Sometimes it is observed that ABC stops moving in the direction of global optimum despite the fact that the population has not congregate to a restricted most advantageous. It can be experiential to facilitate the solution investigation equation of ABC is fine at exploration, however pitiable at exploitation. For that reason, it is enormously enviable to develop a new approach which is able to exploit better solutions in its neighborhood and also able to explore the search space for less fit solutions in order to uphold the appropriate balance among exploration and exploitation activities of ABC.

The ABC metaheuristic technique is stimulated through the spontaneous food foraging behavior of the honey bee creature. Honey bee insect most intuitive creation of nature; it shows combined intellectual behavior at the same time as penetrating the food. The honey bee can memorize the ecological circumstances, can accumulate and distribute the information and can decide according to these observations. As per the changes in the surroundings, the bee updates its position, assign the responsibilities dynamically and go on further by means of societal erudition and education. This extraordinary conduct of honey bees motivates research scientists to imitate the intellectual food foraging behavior of the bees.

Phases of ABC Algorithm: The investigation process of ABC has three key steps:

- Employ the employed bees to a source of food and compute its amount of nectar;
- According to information collected from employed bees, the onlooker bees select the food sources and calculate approximately their quality of nectar;
- Discover the scout bees and take advantage of them on promising food sources for the purpose of exploitation.

Step by Step Procedure of ABC

Step 1 Initialize the Food Source

The algorithm starts with randomly producing food source sites that correspond to the solutions in the search space. Produce the initial food source FSi (i = 1, 2, 3 … n) where n indicates the number of food source. This procedure is called initialization process.

Step 2 Fitness evaluation

Using fitness function, the fitness value of the food source is computed to find the best food source. It is demonstrated as below,

$$Fitness\ function: fit_i = \begin{cases} \dfrac{1}{1+f_i} & if\ fi \geq 0 \\ 1+abs(fi) & if\ fi < 0 \end{cases}$$

Step 3 Employed bee phase

Cycle =1

In the employed bees phase, each employed bee finds a new food source.

υi, j = xi, j + Φij(xi, j - xk, j) with this formula, produce a new solution.

k=1 //k is a random selected index.

j=0 //j is a random selected index.

Φ is randomly produced number in the range [-1, 1].

Step 4 Fitness evaluation for new food source

Fitness values are found for every new food source and choose the best food source.

Calculate f(υ0) and the fitness of õ0.

Step 5 Greedy selection process

Apply greedy selection between x0 and υ0

If x0 < υ0 the solution couldn't be improved, increase its trial counter.

After choosing the best food source next use greedy selection process. Using the equation find the probability of the chosen food source is calculated.

$$p_i = \frac{fit_i}{\sum_{i=1}^{CS/2} fit_i}$$

Step 6: Onlooker bees phase

Produce new solutions υi for the onlookers from the solutions xi selected then depending on pi and evaluate them.

Calculate f(υ2) and the fitness of υ2. Apply greedy selection between x2 and υ2

Memorize the best food source

Step 7: Scout bee phase

For instance, Control Parameters of ABC Algorithm are set as;

- Colony size, CS = 6
- Limit for scout, L = (CS*D)/2 = 6 and dimension of the problem, D = 2

If there is an abandoned solution (the solution of which the trial counter value is higher than L = 6); generate a new solution randomly to replace with the abandoned one.

Cycle = Cycle+1

The procedure is continued until the termination criterion is attained.

Cuckoo Search Algorithm: Cuckoo search (CS) is an optimization algorithm developed Xin-she Yang and Suash Deb in 2009. Each egg in a nest represents a solution and a cuckoo egg represents a new solution. The aim is to use the new and potentially better solutions (cuckoos) to replace a not-so-good solution in the nests.

The three basic principles are:

- Each cuckoo lays one egg at a time and dumps its egg in a randomly chosen nest.
- The best nests with high quality of eggs will carry over to the next generation.
- The number of available host nests is fixed and the host bird finds the egg laid by the cuckoo having fixed probability. The random walks and the L_vy flights are applied in the calculation of the new solutions of the generic equation. Here the random walks are linked with the similarity between a cuckoo's egg and the host's egg. An important issue is the applications of Levy flights and random walks in the generic equation for generating new solutions. The step size S determines how far a random walker can go for a fixed number of iterations. If s is too large, then the new solution generated will be too far away from the old solution (or even jump out side of the bounds). Then, such a move is unlikely to be accepted. If s is too small, the change is too small to be significant and consequently such search is not efficient. So a proper step size is important to maintain the search as efficient as possible.

This constraint is met by applying the L_vy flight as the step size. For the calculation of this step size Mantegna's algorithm is used.

$$S = \frac{\tau r2}{td}$$

S: L_vy step-size in the dimension space d and t is the time taken to cover the average distance of r in dimension space d.

Modified ABC Algorithm: We have considered the Cuckoo search algorithm to modify the ABC algorithm. In ABC, the solutions represent the food sources and the nectar quantity of the food sources corresponds to the fitness of the associated problem. The number of employed and onlooker bees are same and this number is equal to the number of food sources. In our ABC, instead of Onlooker bee we use cross over and mutation operation for the updating the of solution randomly. The various steps involved in implementing ABC algorithm is explained below.

ABC - CS Algorithm Steps

Step 1 Initialize the food source

The algorithm starts with randomly producing food source sites that correspond to the solutions in the search space. Produce the initial food source FSi (i = 1, 2, 3 … n) where n indicates the number of food source. This procedure is called initialization process.

Step 2 Fitness evaluation

Using fitness function, the fitness value of the food source is computed to find the best food source. It is demonstrated as below,

$$\text{fitness} = \max \text{PSNR} \tag{1}$$

Step 3 Employed bee phase

In the employed bees phase, each employed bee finds a new food source new FSij in the neighborhood of its current source FSi. The new food source is calculated using equation number (2).

$$FSij = FSij + \gamma\,(FSij - FSkj) \tag{2}$$

where FSij is the jth parameter of the ith employed bee; new FSij is a new solution for FSij in the jth dimension; FSkj is the neighbor bee of FSij in employed bee population; γ is a number arbitrarily chosen in the range of [–1, 1].

Step 4 Fitness evaluation for new food source

Fitness values are found for every new food source and choose the best food source.

Step 5 Greedy selection process

After choosing the best food source next use greedy selection process. Using the equation (3), find the probability of the chosen food source is calculated.

$$p_i = \frac{fit_i}{\sum_{i=1}^{CS/2} fit_i} \tag{3}$$

where fitness of i is a fitness value of ith employed bee.

Step 6 Instead of onlooker bee we use CS

After calculating the probability of the employed bee we will update values in CS algorithm. The steps are given below.

Step 1 Initialization phase: The population (mi, where i = 1, 2, … n) of host nest is started arbitrarily.

Step 2 Generating new cuckoo phase: Using levy flights a cuckoo is selected at random and it produces new solutions. After that the produced cuckoo is evaluated using the objective function for finding out the quality of the solutions.

Step 3 Fitness evaluation phase: Evaluate the fitness function based on the equation and next select the best one.

$$\text{fitness} = \text{maximum popularity} \tag{4}$$

Step 4 Updation phase: Improve the initial solution by levy flights in which cosine transform is used. The superiority of the new solution is evaluated and a nest is selected among arbitrarily. If the excellence of new solution in the selected nest is better than the old solutions, it will be replaced by the new solution (Cuckoo) Otherwise, the previous solution is placed aside as the best solution. The levy flights employed for ordinary CS algorithm is,

$$m_i^* = mi^{(t+1)} = m_i^{(t)} + \alpha \oplus Levy(n) \tag{5}$$

Step 5 Reject worst nest phase: The worst nests are thrown away in this part, based on their chance values and new ones are built. Presently, function the best solutions are ranked based on their fitness. After that the best solutions are identified and spotted as optimal solutions.

Step 6 Stopping criterion phase: Till the maximum iteration achieves this process is repeated. The optimized effect will be inspected for extract a significant rule.

Scout Bee Phase: The abandonment counters of all employed bees are tested with a number which is decided by designer (limit). The employed bee, which cannot improve self-solution until the abandonment counter reaches to the limit, becomes scout bee. The scout bee in which a solution was produced by itself to become an employed bee. Therefore, scout bees in ABC algorithm prevent stagnation of employed bee population. Finally, utilizing these rules we are extracted a significant set of rule from that rules we are extracting optimal knowledge from the dataset via. Rules, the data will be classified using fuzzy classifier.

Comparative Study with Metrics: An evaluation metric is used to evaluate the effectiveness of the proposed system. It consists of a set of measures that follow a common underlying evaluation methodology some of the metrics that we have choose for our evaluation purpose are True Positive, True Negative, False Positive and False Negative, Accuracy, F measure.

Accuracy: Accuracy of the proposed method is the ratio of the total number of TP and TN to the total number of data.

$$Accuracy = \frac{TN + TP}{(TN + TP + FN + FP)} \tag{12}$$

Experimental Outcome Condition as determined by the Standard of Truth

Comparative Analysis: The comparison of Accuracy values of the existing ABC method works with the proposed work of ABCCS to show that our proposed work is better than the state-of-art works. We can establish that our proposed work helps to attain very good accuracy for the attack prediction of database using Fuzzy. And also we can establish this prediction accuracy outcome by comparing other classifiers. We have utilized ABC for our Comparison in our work. The Comparison outcomes are presented in the following Table 3.

The Accuracy for the ABC are 0.702975207, 0.803801653 and 0.880165289, which is low in compared with our classifier, Fuzzy for four datasets are 0.793553719, 0.89785124 and 0.929090909.

Table 1: Condition and terms of TP, TN, FT and FN

	Positive	Negative
Positive	TP	FP
Negative	FN	TN

Table 2: ABCCS and ABC values of TP, TN, FT and FN.

ABCCS			ABC		
TP	TN	FP	TP	TN	FP
4127	564	544	2665	1388	1536
4408	910	458	4318	505	15
5145	456	304	4340	985	81

Table 3: Comparison of Accuracy values in ABCCS vs ABC

Iteration	ABCCS Accuracy values	ABC Accuracy Values
50	0.793553719	0.702975207
75	0.89785124	0.803801653
100	0.929090909	0.880165289

Table 4: Comparison of ABCCS Method Vs ABC Method

Metrics	ABC-CS%	ABC%
Accuracy	83	76

The above specified explains the comparison outcomes of the ABCCS method with ABC method. The improved good accuracy outcomes of attack classification are presented in the ABCCS work. In comparison with the ABC gives very less accuracy values for the evaluation measures. The accuracy values of ABC give 76% but ABCCS gives 83%. From these outcomes, by means of Fuzzy classifier in the work classify the attack and normal as it gives improved accuracy outcomes.

CONCLUSION

In the recent trend we are all very much concerned and focused on performance of accuracy. The major issue while solving complex real world problem from almost each and every field of life demands for accurate optimizers. The ABC algorithm is one of the easiest and simple swarm intelligence algorithms that offer good result with accuracy for optimization problems with different level of complexity. The ABC algorithm proves that it is best choice when tested for standard benchmark problems and complex real world problem. It can be applied for large class of problems. The ABC algorithm has some drawbacks also, as sometimes it suffers from premature convergence or stagnation that results in loss of balance between intensification and diversification capabilities. This paper First, it describes the cooperative behaviour of honey bees and then the imitation of honey bees for artificial bee colony algorithms is shown. Secondly from the ABC algorithm is modified with the Cuckoo Search within the phases of ABC. The results produced by ABC algorithm are compared with the results obtained by the combination of ABC and Cuckoo Search. The final comparison of the performance in accuracy is very much improved in ABCCS with the ABC of population-based algorithm.

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