IJSRD - International Journal for Scientific Research & Development| Vol. 1, Issue 9, 2013 | ISSN (online): 2321-0613

A Novel Approach of Image Ranking based on Enhanced Artificial Bee Colony Algorithm

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Abstract—In recent years researchers have provided novel problem solving techniques based on swarm intelligence for solving difficult real world problems such as traffic, routing, networking, games, industries and economics. Artificial bee colony algorithm (ABC) was first developed by Dervis Karaboga [1]. When the robust performance is desired by means of searching something, the swarms does it better; by adaptation of greedy selection and random search. The ABC algorithm simulates the foraging behavior of honey bees. The local search in two stages in each step and global search are responsible for making this algorithm a robust search technique. The details of this algorithm are discussed here. Because of its very strong search process, computational simplicity and ease of modification according to the problem, the ABC algorithm is now finding more widespread applications in business, scientific and engineering circles. In this paper, we provide a thorough and extensive overview of most research work focusing on the application of ABC, with the expectation that it would serve as a reference material to both old and new, incoming researchers to the field, to support their understanding of current trends and assist their future research prospects and directions. Also new proposed architecture of Enhanced ABC algorithm for image ranking is also given here.

Key words: Swarm Intelligence, Artificial Bee colony Algorithm, ranking techniques.

I. INTRODUCTION

Classical optimization techniques impose several limitations on solving mathematical programming and operational research models. In order to overcome the drawbacks of the classical optimization techniques, researchers around the globe started thinking about several unconventional optimization methods for solving combinatorial and numerical optimization problems. These algorithms can be classified into several groups depending on the criteria being considered [1], such as population based, iterative based, stochastic, deterministic etc. Continuous improvement and development in the field of optimization techniques causes to classify the population based algorithm again to two subdivisions i.e. evolutionary algorithms (EA) and swarm intelligence based algorithm [1]. A very common example of EA is genetic algorithm. In recent years, swarm intelligence based algorithm has become a research interest to many scientists. Swarm intelligence is based on social-psychological principles and provides insights into social behavior of insects. Bonabeau et. al. [2] defined the swarm intelligence as 'any attempt to design algorithms or distributed problem solving devices inspired by the collective behavior of social bee colonies and other animal societies'. Figure 1 depicts different types of swarm

Fig. 1 : Swarm of bees, ants and fishes

Two fundamental concepts, i.e. (a) self-organization and (b) division of labor, are necessary and sufficient properties to obtain swarm intelligence behavior such as distributed problem solving systems that self-organize and adapt to the given environment. Bonabeau et al. [2] characterized four basic properties on which self- organization relies: i) Positive feedback, ii) negative feedback, iii) fluctuations and iv) multiple interactions. It is already stated that bees swarming around their hive during food pouching is a very good example of swarm intelligence. Observation and studies on honey bees' behavior have resulted in a number of optimization techniques and algorithms for solving the combinatorial type of problems.

The remaining parts of the paper are organized as follows: The Foraging Behavior of Bees in Nature is briefly outlined in Section II, while the complete ABC algorithm and its merits and demerits are discussed in Section III. Section IV Comparison of ABC with other traditional techniques, while section V gives Proposed architecture of our ranking algorithm Finally, the conclusion and future research directions in terms of the applications of ABC to optimization problems are outlined in Section

II. FORAGING BEHAVIOR OF BEES IN NATURE

Ball once (in 1999) said that bees were 'blindingly using the highest mathematics by divine guidance and command'. He was rightly so. The foraging process of honey bees can be better understood using Figure 2. At the very beginning as there is no information about the probable food sources, some scout bees are set free to search for some food sources. As soon as a scout bee finds a food source, it becomes an employed bee. It returns to the hive, unloads some nectar and performs waggle dance to attract the onlooker bees. Suppose, there is having two discovered food sources, e.g. A and B. The corresponding employed bees perform waggle dances in the specified area. Attracted by that waggle dance, some onlookers engage themselves in the food sources, A and B. Now each time an employed bee while returning to the hive for unloading nectar, is having two options either it may dance to attract more onlookers (EF1) or continue foraging by itself without attracting any more onlooker (EF2). Now as soon as the nectar amount of a food source is finished, that food source is called off. The employed bees corresponding to that food source become unemployed foragers having two options either to search for a new food source (become a scout) or to stay in the hive and get attracted by the waggle dance of other employed bees (become an onlooker). This process continues in the same way. It can be noted that in the foraging behavior of honey bees, three parameters are of prime importance, i.e. a) food source, b) employed foragers, and c) unemployed foragers and the foraging behavior again leads to two modes, i.e. a) recruitment of nectar source, and b) abandonment of nectar source.[3]

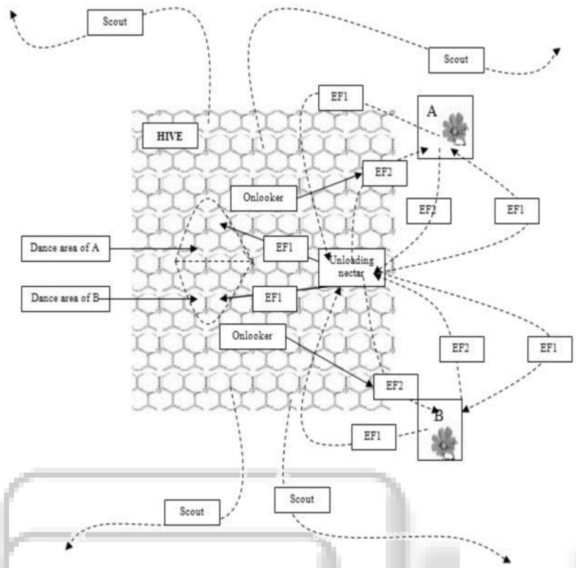

Fig. 2 : Foraging process of honey bees

From the above stated discussion, it is very important to note the process of information sharing among the honey bees. The employed bees while returning to the hive having information about the food source, shares the information with nest-mates by performing a dance in some specified area, called the waggle dance. While performing the waggle dance, the direction of bees indicates the direction of the food source in relation to the sun, the intensity of the waggle dance indicates how far away it is and the duration of the dance indicates the amount of nectar on related food source. Waggle dancing bees that have been in the hive for an extended time, adjust the angles of their dances to accommodate the changing direction of the sun. The onlooker bees, which are waiting in the hive, are attracted by the dancing of the employed bees and get engaged in unloading the nectar. The number of onlooker bees that will be attracted on a single food source depends upon the waggle dance performed by the employed bees. The waggle dance of the employed bees is shown in Figure 3.

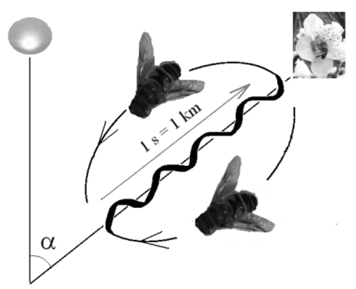

Fig. 3: Waggle dance of honey bee

In the case of honey bees, the basic properties on which self-organization rely are as follows:

a) Positive feedback: As the nectar amount of food sources increases, the number of onlookers visiting them increases, too.
b) Negative feedback: The exploration process of a food source abandoned by bees is stopped.
c) Fluctuations: The scouts carry out a random search process for discovering new food sources.
d) Multiple interactions: Honey bees share their information about food source positions with their nest mates on the dance area.[4]

III. THE ABC ALGORITHM

The ABC consists of four main phases

A. *Initialization Phase:*

The food sources, whose population size is SN, are randomly generated by scout bees. Each food source, represented by $\boldsymbol{x_m}$ is an input vector to the optimization problem, $\boldsymbol{x_m}$ has D variables and D is the dimension of searching space of the objective function to be optimized. The initial food sources are randomly produced via the expression (3.1)

$$x_m = l_i + rand(0,1) * (u_i - l_i) \quad (3.1)$$

Where u_i and l_i are the upper and lower bound of the solution space of objective function, rand (0, 1) is a random number within the range [0, 1].

B. *Employed Bee Phase:*

Employed bee flies to a food source and finds a new food source within the neighborhood of the food source. The higher quantity food source is memorized by the employed bees. The food source information stored by employed bee will be shared with onlooker bees. A neighbor food source $\boldsymbol{v_{mi}}$ is determined and calculated by the following equation (3.2)

$$v_{mi} = x_{mi} + \emptyset_{mi}(x_{mi} - x_{ki}) \quad (3.2)$$

Where i is a randomly selected parameter index, x_k is a randomly selected food source, $\emptyset_{mi}$is a random number within the range [-1, 1]. The range of this parameter can make an appropriate adjustment on specific issues. The fitness of food sources is essential in order to find the global optimal. The fitness is calculated by the following formula (3.3), after that a greedy selection is applied between $x_m$andv_m.

$$fit_m(x_m) = \begin{pmatrix} \frac{1}{1+f_m(x_m)}, f_m(x_m)>0 \\ 1+|f_m(x_m)|, f_m(x_m)<0 \end{pmatrix} \quad (3.3)$$

Where $f_m(x_m)$ is the objective function value ofx_m.

C. *Onlooker Bee Phase:*

Onlooker bees calculates the profitability of food sources by observing the waggle dance in the dance area and then select a higher food source randomly. After that onlooker bees carry out randomly search in the neighborhood of food source. The quantity of a food source is evaluated by its profitability and the profitability of all food sources. *Pm* is determined by the formula

$$p_m = \frac{fit_m(x_m)}{\sum_{m=1}^{SN} fit_m(x_m)} \quad (3.4)$$

Where$fit_m(x_m)$ is the fitness of x_m.

Onlooker bees search the neighborhood of food source according to the expression (3.5)

$$v_{mi} = x_{mi} + \emptyset_{mi}(x_{mi} - x_{ki}) \quad (3.5)$$

D. Scout Phase:

If the profitability of food source cannot be improved and the times of unchanged greater than the predetermined number of trials, which called "limit", the solutions will be abandoned by scout bees. Then, the new solutions are randomly searched by the scout bees. The new solution x_m will be discovered by the scout by using the expression (3.6)

$$x_m = l_i + rand(0,1) * (u_i - l_i) \quad (3.6)$$

$rand(0,1)$is a random number within the range [0,1], u_i and $\boldsymbol{l_i}$ are the upper and lower bound of the solution space of objective function.[5]

The pseudo code of the ABC algorithm is given bellow:

ABC algorithm

1. Initialize the population of solutions xijk (i = 1,2,. . .SN, j = 1,2,. . .D, k=1,2,....V).
2. Evaluate the population.
3. Cycle = 1.
4. Repeat.
5. Produce new solutions _ijk for the employed bees by using Eqn. (1.2) and evaluate them.
6. Apply the greedy selection process.
7. Calculate the probability value pi for the solutions using Eqn. (1.1).
8. Produce the new solutions for the onlookers depending on pi values and evaluate them.
9. Apply the greedy selection process.
10. Determine the abandoned solution for the scout, if exists and replace it with a new randomly produced solution xijk using Eqn. (1.3).
11. Memorize the best solution achieved so far.
12. Cycle = Cycle+1.
13. Iterate until cycle = MCN.

Strengths of the ABC Algorithm

1) ABC is very much flexible and can easily be modified according to the problem. Moreover, this method can easily be applied to various problems.[21]
2) In the ABC algorithm, the local search in two stages (by the employed bees and by the onlooker bees) in each cycle, and the global search when the process stuck to the local optima (by means of scouts) make the search process very strong.[23]
3) The ABC algorithm is quite robust It also does not require the user to specify any starting point.[21]
4) This algorithm also performs quite well when there are lots of local optima to avoid.[22]
5) The positive feedback in the ABC algorithm accounts for rapid discovery of good solutions.[2]
6) The ABC algorithm employs distributed computation, which avoids premature convergence.[23]
7) The greedy heuristic used in the ABC algorithm helps find an acceptable solution in the early stages of the search process.[6]

Weaknesses of the ABC Algorithm

1) There does not exist any standard software for the ABC algorithm as well.[1]
2) The ABC algorithm requires the user to fiddle with several parametric settings, such as swarm size and limit.[1]
3) This algorithm has slower convergence than other heuristic-based algorithms.[3]
4) There is no centralized processor to guide the bees system towards good solutions.[4]

IV. COMPARISON OF ABC WITH TRADITIONAL TECHNIQUES

With huge amount of digital images being continuously acquired and archived, large volumes of raw data is being generated. Extracting relevant information from these is becoming a challenging work. Ranking is an important tool in feature retrieval from large datasets.

The problem of image ranking has been solved by using the traditional classical approaches like Parallelepiped Classification [28], Minimum Distance to Mean Classification [28], Maximum Likelihood Classification [28] etc. However these techniques show limited accuracy in information retrieval and high resolution image is needed. Nature inspired computing techniques are a recent trend and were introduced in remote sensing for image ranking. The principal constituents of soft computing techniques are fuzzy logic [29], rough set theory [30], neural network theory, and probabilistic reasoning and Swarm Intelligence techniques [31]. However the soft computing techniques like the fuzzy classifier [29], and the rough set classifier [30] were not able to provide good result in case of ambiguity since the aim of these techniques was to synthesize approximation of concepts from the acquired data. Hence these techniques did not provide very much accurate results with low spatial resolution images. Also these techniques were not able to handle the crisp and continuous data separately.

The solution to the above drawbacks was provided by recently introduced concept of swarm intelligence [30] which comes under natural computation.

I have developed Enhanced Artificial Bee Colony Algorithm for land cover feature recognition. It is a pixel wise approach like membrane computing [28] but it uses less parameter and is able to achieve better accuracy. The aim of this work is to highlight the potential of nature inspired swarm techniques in building efficient optimization models.

V. PROPOSED ARCHITECTURE OF OUR RANKING ALGORITHM

Based on comparative survey it is clear that ABC can solve drawbacks of the other ranking technique. Here I have given proposed architecture of my ranking algorithm and it will give promising results in classification.

Stage 1: Input Multispectral Image

This is the very first stage where the input is fed to the system. For ranking problem we have considered any multispectral image. The images are input as '.tif' format and are read using function imread() in matlab.

Stage 2: A- Generate training data set

Our algorithm is a supervised one where we need some already classified expert's data to train our EABC algorithm.

This data is generated by some experts, in our case by scientists at DTRL laboratory at DRDO. This is also the second major input in our classifier. The training dataset is in form of excel sheets with some random pixel information of each band and the feature they belong.

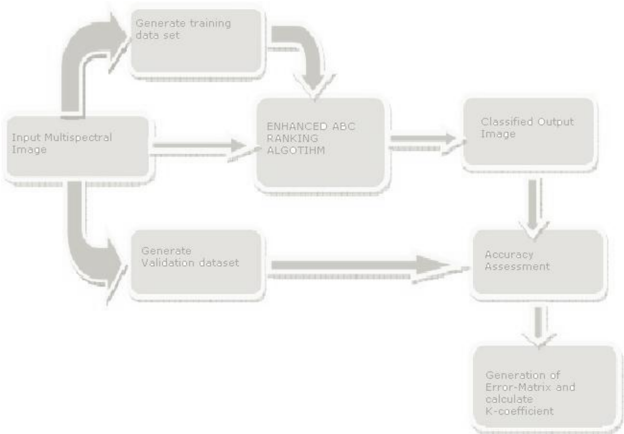

Fig. 4 : Architecture of Proposed Ranking Algorithm

B - Generate Validation dataset

A validation set is required to validate our classification results. This is also generated from the multispectral image by the experts. It is very much alike the training set just that is not input into the system but used for verification.

Stage 3: EABC ranking algorithm

This is the core stage of our entire process where the input image is processed using the training dataset. Our proposed algorithm is implemented here for the ranking process of the image and we get the processed output image.

Stage 4: Classified Output Image

This is the output of our algorithm. The important features of the input multispectral image are extracted and given different colour codes for distinguish-ability. All the pixels of the image hence get unique colour for representation. This new ranked image is then displayed in matlab output.

Stage 5: Accuracy Assessment

This is an important stage where the validation and accuracy checking of our ranked output is done. The validation dataset is the other input for this stage. Here all the pixels contained in the validation set are checked with our algorithm. It is seen whether the algorithm correctly classifies those pixels or not. Since these pixels are marked by experts we can assess the accuracy of the algorithm.

Stage 6: Construction of error matrix and calculating kappa coefficient

This can be called as a part of accuracy assessment, but shown is done after validation data set is acted upon by our algorithm. We generate an Error matrix which determines quantitatively that how pixels are correctly absorbed in their required features. Error matrices compare, on category-by category basis, the relationship between known reference data (ground truth) and the corresponding results of an automated ranking. We also find the kappa coefficient. It serves as an indicator of the extent to which the percentage correct values of an error matrix are due to "true" agreement versus "chance" agreement.

VI. CONCLUSION

In this paper, variety of research article in the domain of ABC has studied. From the in depth literature survey, it is observed that a large part of research was concentrated towards modifying the ABC algorithm to solve a variety of problems, including engineering design problems, scheduling problems, data miming problems etc. Although ABC has great potential, it was clear to the scientific community that some modifications to the original structure are still necessary in order to significantly improve its performance. Further, in this paper I have given a novel swarm based Enhanced ABC approach for image ranking, the proposed work focuses on extracting the important features from image using artificial bee colony. ABC works on single unit of object that is; it processes the image pixel wise thus it focuses on heterogeneous issues more prominently. Our proposed algorithm is flexible enough to classify any feature very efficiently as none of the parameters are dependent on feature type and hence can be adapted according to the application. The proposed algorithm is applied to two different images and in both of them it has shown efficient and good results. In conclusion, ABC remains a promising and interesting algorithm, which would be used extensively by the researchers across diverse fields.

ACKNOWLEDGMENT

The satisfaction and euphoria that accompany the successful completion of any task would be incomplete without the mention of the people who made it possible, whose consistent guidance and encouragement crowned my efforts with success. Nidhi Gondalia highly thankful to my guide Foram Joshi and Nirali Makad without whose guidance the work would not have been materialized and she helps me to solve my difficulties arising during this paper writing. Also N. B. Gondalia would like to acknowledge all other faculty member of Computer Department and my classmates who have come forward to help me in every way at any time. With all this assistance little for remains for which I can take credit.

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