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Bespoke Artificial Bee Colony Algorithm to Determine the Earthquake locations

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Abstract –Metaheuristic algorithms are achieving a great success and gaining the attention of many researchers, to solve or optimize real world problems. In the present study we focus on recently proposed metaheuristic that mimics the foraging behaviour of honeybees called artificial bee colony algorithm (ABC). ABC consist of three groups of bees namely employed, onlooker and scout bees. Likewise other metaheuristic algorithms ABC is good in exploration while poor in exploitation while foraging for food source. A poor balance between exploration and exploitation may result in a weak optimization method which may cause premature convergence, trapping in a local optima, and stagnation. In this paper we tried to improve the exploitation capability which in turn accelerates the convergence of ABC by modifying the onlooker bee phase. The modified variant called BABC is applied to determine the seismic location in the Earth's crust and upper mantle.

Keywords – Metaheuristic; Artificial Bee Colony; Exploitation; Convergence; Earthquake; Hypocenter

1. Introduction

Artificial bee colony algorithm (ABC) a recently proposed metaheuristic proposed by Karaboga [1] based on intelligent foraging behavior of honey bee swarm. It's gradually increasing interest of many researchers because of its simplicity, outstanding performance, wide applicability and fewer control parameters. The basic ABC has been compared with other population based evolutionary algorithms, such as GA, PSO, and DE [2][3]. ABC has been used to solve real-word problems, discussed in next section. However like other evolutionary algorithms ABC also faces some limitations while handling complex multimodal functions, functions having narrow curve valley and its stochastic nature slows down the convergence speed [4]. The reason behind all this is improper balance between exploration and exploitation. ABC is good at exploration but poor at exploitation [5]. A number of ABC variants have been proposed to achieve these two goals and are also discussed in next section.

In this paper, Onlooker phase of ABC is modified by embedding the concept of greedy bee inspired by [6].The proposed variant is named as BABC.

The rest of the paper is organized as follows: section 2 literature survey of ABC and methods of finding earthquake locations are given. In section 3, the earthquake problem is discussed. The proposed BABC is described in section 4. In section 5, experimental settings and results are given. Finally the conclusions are given in section 6.

2. Survey of Literature

2.1. Artificial Bee Colony

Applications of ABC

ABC has been used to solve real-word problems such as flow shop scheduling problems [6], minimum spanning tree problems [8], parameter estimation problems [9], solving engineering design problems [10], parameter estimation of software reliability growth models [11], parameter estimation in engineering problems [12], image processing [13] and applied to number of real application in many streams of finance, supply chain system, medical etc.

Various variants of ABC

Accelerating convergence speed and avoiding the local optima have become two important and appealing goals in ABC research. A number of ABC variants have, been proposed to achieve these two goals [14]-[20]. The comprehensive survey of ABC can be found in [21].

2.1. Methods of Finding Earthquake Locations

The earthquake location can be traced out by numerous methods depending upon the different velocity models of seismic waves in the Earth crust. Most of them in the standard catalogs are still using traditional least square methods, one reason for this is a desirable conservatism in the production of catalogs, whose value is derived from their consistency, which makes it to possible to compare seismicity patterns at different times without the possible biasing effects of a change in the location methods.

The most challenging thing while finding an Earthquake location is the heterogeneity of the Earth's crust. Due to this heterogeneity of Earth crust it is a very difficult for seismologists to study the average crustal velocity of the seismic waves. There are several velocity models developed for the average crustal velocity of the seismic waves at different depths of the Earth crust in the Himalayan region [22]-[26]. According to [26] the velocity of the compressional waves with in the depth 0-15 Km is 5.2 Km/sec and 15-40 Km is 5.89 Km/sec. According to [23] the velocity of compressional wave within the depth 40-70 Km is 8.14 Km/sec, 70-85 Km is 8.32 Km/sec and 85-100 is 8.29 Km/sec.

One way to solve the problem of determining Earthquake is to model the problem as a nonlinear optimization problem in which the objective function to be minimized is the discrepancy between the observed travel times and calculated travel times. Earlier [27] used a random search technique to solve the problem.

3. Mathematical Model

The mathematical model for determining earthquake location may be predicatively described in two components, as a forward problem model and second one as a inversion problem model. Both are discussed below.

3.1 First Problem Model (Forward)

Travel time model may be called forward model, which analyze the travel time of the compressional wave in the different layers of the Earth crust. As stated above the travel time of the compressional waves in the different layers of the Earth using the velocity model (1) will be calculated for different depths, then the travel time of seismic waves in each layer to get the total travel time for the waves will be added to reach at the observational stations on the surface of the Earth from focus. Let the parameters of the hypocentre be (x_i, y_i, z_i), where they represent the coordinate values of latitude, longitude and depth of the preliminary hypocentre. (x_j, y_j) be the latitude and longitude of the stations. v_l is the average crustal velocity of the Compressional waves in the l^{th} layer of the Earth. The theoretical travel time and epicentral distances according to [28], are given by:

$$t_{ij} = \frac{\sqrt{\Delta_{ij}^2 + z_i^2}}{v_l} \tag{1}$$

Where

$$\Delta_{ij} = 111.199\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 \cos^2 \frac{(x_i - x_j)}{2}}$$

3.2 Second Problem model (Inverse)

In this model the values of hypocentral parameters will be calculated inversely by minimizing a root mean square function of calculated and observed travel times. Let C_k and O_k represents the calculated and observed travel times and equation (2) gives the root mean square function of C_k and O_k which we have to minimize:

$$Minimize\ f = \{\sum_{i=1}^{n}(C_k - O_k)^2\}^{1/2} \tag{2}$$

For a single Earthquake our C_k will be

$$C_k = \frac{\sqrt{\Delta_k^2 + z_k^2}}{v_l} \tag{3}$$

Where

$$\Delta_{ij} = 111.199\sqrt{(x - x_i)^2 + (y - y_i)^2 \cos^2 \frac{(x - x_i)}{2}}$$

Here (x,y,z) is the hypocentre of the Earthquake. In order to validate the model, real data from NW Himalayas is considered. Therefore to physically validate the model it is necessary to incorporate the following restrictions:
Latitude lower < x < Latitude upper;
Longitude lower < y < Longitude upper;
Depth lower < z < Depth upper.
As we are finding the hypocenters in the NW Himalayan and Hindukush region. These restriction limits are taken as

$$22^0 < x < 36^0;\ 68^0 < y < 98^0;\ 0 < z < 100(\text{Kms})$$

4. ABC and Proposed Variant BABC

4.1 ABC

In ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, unemployed bees (onlookers and scouts) The scout bees randomly search the enviroment surrounding the hive for new food sources and this behavior is a kind of fluctuations which is vital for self-organization. The outlookers waiting in the hive find a food source by means of information presented by employed foragers. The mean number of scouts is about 5 –10% of the foragers. In ABC, first half of the colony consists of employed artificial bees and the second half constitutes the artificial onlookers. The employed bee whose food source has been exhausted becomes a scout bee. In ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees is equal to the number of food sources, each of which also represents a site, being exploited at the moment or to the number of solutions in the population. In ABC optimization, the steps given below are repeated until a stopping criterion is satisfied.

1. Each employed bee determines a food source, which is also representative of a site, within the neighborhood of the food source in her memory and evaluates its profitability.

$$P_i = f_i / \sum_{K=1}^{SN} f_k \quad (1)$$

where f_i is the fitness value of a i, food source (position in parameter space). In other words onlookers will explore promising locations with higher probability than others.

2. Each employed bee shares her food source information with onlookers waiting in the hive and then each onlooker selects a food source site depending on the information taken from employed bees.

$$V_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (2)$$

where $i, k = 1,...,SN$, $j = 1,...,n$, and v_i is the new food source generated by using both, the current food source x_i and a randomly chosen food source x_k from the population and $-1 \le \phi_{ij} \le 1$ (generated at random every time it is used) determines the step size of the movement. Both, i and j are generated at random but $k \ne i$.

3. Each onlooker determines a food source within the selected site by herself and evaluates its profitability.

4. Employed bees whose sources have been abandoned become scout and start to search a new food source randomly.

$$X_{ij} = x_{\min,j} + rand(0,1)(x_{\max,j} - x_{\min,j}) \quad (3)$$

where i = 1,2,..,SN. j = 1,2,…,n. $x_{max,j}$ and $x_{min,j}$ are upper and lower bounds of parameter j, respectively. These food sources are randomly assigned to SN number of employed bees and their finesses are evaluated.

4.2 BABC: Proposed variant

The objective of this study is to enhance the working of basic ABC by producing efficient food sources which in terms of ABC implies to the solution vectors having better fitness value. Also, we aim to develop a scheme which is able to exploit the local information efficiently and is easy to apply.

One of the simplest ways to search the solution space can be done by linear exploitation. In the proposed study, two schemes are considered. In the first scheme the new solution vector (food source) is generated by taking arithmetic mean of the convex linear combination of three mutually exclusive solution vectors.

The convex linear combination of three vectors is given as:

$$V_0 = \sum_{i=1}^{3} \lambda_i X_{r1,G}$$

where the weights, $\lambda_i \ge 0$ and $\sum_{i=1}^{3} \lambda_i = 1$.

Arithmetic Mean of solution V_0

$$V_1 = \frac{1}{3} \sum_{i=1}^{3} \lambda_i X_{r1,G} \quad (4)$$

In this paper we embed the above equation in onlooker phase to search the food source as discussed below:

$$V_{ij} = (x_{r1,j} + x_{r2,j} + x_{r3,j})/3 + \phi_{ij}(x_{best,j} - x_{k,j}) \quad (5)$$

where $r_1 \ne r_2 \ne r_3 \ne i \in [1, SN]$ are selected randomly and x_{best} is the best food source, which makes it greedy towards the food source

5. Experimental Settings and Results

5.1 Experimental Settings

- The main parameters of ABC are: the colony size (SN), MCN (Maximum Cycle Numbers) and “limit” which have been carefully fine tuned after conducting a series of experiments.
- All algorithms are implemented in Dev C++ and the experiments are conducted on a computer with 2.00 GHz Intel (R) core (TM) 2 duo CPU and 2- GB of RAM.
- In order to make a fair comparison of ABC and the proposed algorithm, we fixed the same seed for random number generation so that the initial population is same for all the algorithms.
- For each problem, the ABC and BABC variants are independently run 30 times.
- The parameter setting is taken as follows:

Population size	*100 (i.e SN=50)*
limit	*100*
Value to Reach (VTR)	*10^{-15}*
Maximum MCN	*10000*

5.2 Testing of BABC performed on the earthquake data and result analyses

The real data has been taken from the observation of earthquake occurred on 25 September 2008 in Hindu Kush and NW Himalayan region in India to test the performance of BABC. An Earthquake is recorded of intensity 5.0 on Richter scale whose observed location is 28.8890, 85.0130 and depth of 111.6 Km based on this data we have calculated the travel time in each layer of the Earth at different depths to the ten different stations by using eq. (3) from which this data is observed. The data is given in the Table1. Table 2 gives the detailed calculation of travel times different layers. Using the travel time data we minimize the function f.

The comparative results of the PSO [29] and BABC are presented in the Table 3, showing the function values of the hypocentral parameters. The results of PSO are taken from literature and compared that of BABC. Convergence graph demonstrated in Figure 1 shows the significant improvement in the convergence of BABC.

Table 1. Location of earthquake and the locations of observations stations

Hypocenter	Stations	
28.889^0 85.013^0 111.6 km	30.00^0	70.00^0
	30.14^0	79.20^0
	30.97^0	77.86^0
	30.71^0	77.25^0
	31.10^0	79.61^0
	30.54^0	78.10^0
	29.71^0	78.43^0
	30.49^0	77.58^0
	30.53^0	77.73^0
	30.33^0	78.74^0

Table 2. Travel time of Compressional waves at different depths of the earth crust

Travel Times (Sec) in different depths (in Kms)					
0-15	15-40	40-75	75-85	85-100	Total
3.70972	4.71768	3.97535	2.31858	2.32697	17.04830
3.81867	4.78496	4.01723	2.38667	2.39531	17.40284
3.79631	4.77107	4.00857	2.37269	2.38128	17.32992
3.79271	4.76884	4.00718	2.37044	2.37902	17.31819
3.78329	4.76300	4.00354	2.36456	2.37311	17.28750
3.78739	4.76554	4.00512	2.36712	2.37568	17.30085
3.80601	4.77709	4.01232	2.37876	2.38736	17.36154
3.81897	4.78515	4.01734	2.38686	2.39550	17.40382
3.80686	4.77762	4.01265	2.37929	2.38790	17.36432
3.80147	4.77427	4.01056	2.37592	2.38452	17.34674

Table 3. Simulated value of resultant hypocentral parameters

PSO				BABC			
x^0	y^0	z^0	f	x^0	y^0	z^0	f
28.0056	84.0005	110.16	0.000301	28.0027	84.0012	110.01	0.000287
28.0074	84.0029	110.01	0.000422	28.0074	84.0121	110.13	0.000393
28.0001	84.0097	109.87	0.000934	28.0001	84.0172	109.56	0.000828
28.0019	84.0174	109.12	0.000937	28.0015	84.0613	109.78	0.000813
28.0007	84.0652	110.23	0.000600	28.0023	84.0881	110.39	0.000517
28.0001	84.0134	110.33	0.000832	28.0014	84.0445	110.06	0.000723
27.8898	84.0203	110.09	0.000826	27.8812	84.0231	110.73	0.000612
28.4334	84.0304	109.15	0.000921	28.4371	84.0126	109.81	0.000634
28.1245	85.0403	110.13	0.000844	28.1234	85.0234	110.27	0.000791
28.3212	85.0006	110.24	0.000632	28.3213	85.0039	110.74	0.000386

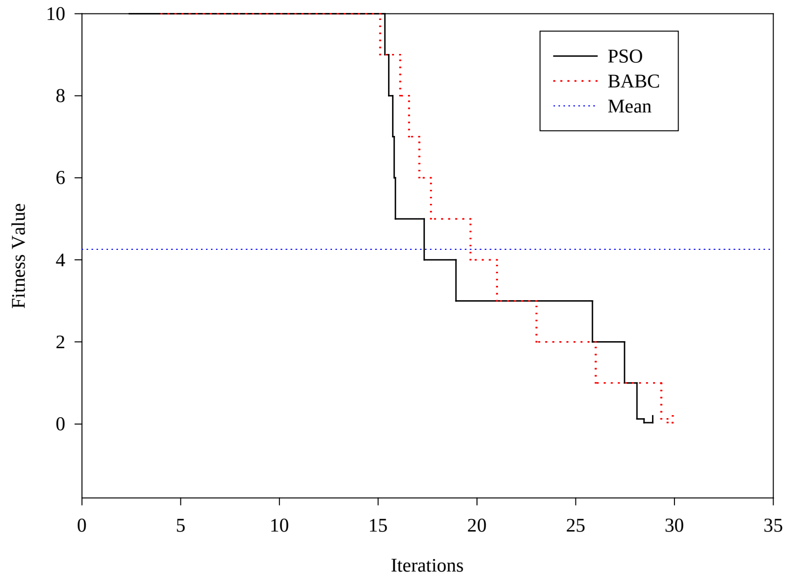

Figure 1. Convergence graph

6. Conclusions

In ABC, the employed bees and onlooker bees carry out exploration and exploitation using the same equation. The performance of ABC greatly depends on single equation. This study presents some modification in the original structure of ABC. To accelerate the convergence of ABC, convex linear combination is embedded in its onlooker phase. And it is tested to identify the ways to determine and improve the seismic locations. The data is taken from the literature. The results of the proposed variant give good results and enhance the accuracy of the hypocentral parameters.

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