iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 2 Issue: VII Month of publication: July 2014

DOI:

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

Artificial Bee Colony algorithm using Structured Swarm

Rajesh Rajaan

Computer Science Department

Abstract: Swarm Intelligence is a meta-heuristic approach in the field of nature inspired techniques that is used to solve optimization problems. It is based on the collective behaviour of social creatures. Social creatures utilize their ability of social learning to solve complex tasks. The swarm intelligence based algorithms which have emerged in recent years includes ant colony optimization (ACO), particle swarm optimization (PSO), bacterial foraging optimization (BFO), artificial bee colony optimization (ABC) etc. In ABC each bee stores candidate solution and modifies its candidate over time stochastically, based on the best solution found by neighboring bees and based on the best solution found by the bee its own experience. When tested over various benchmark function and real life problems, it has performed better than a few evolutionary algorithms and other search heuristics. However ABC, like other probabilistic optimization algorithms, has inherent drawback of premature convergence or stagnation that leads to loss of exploration and exploitation capability. In recent years, many researchers focus and suggested various optimization algorithms based on swarm intelligence. Therefore; this report resented a modified ABC. In the proposed strategy, search process in ABC is performed by smaller group of independent swarms of bees. A new control parameter named perturbation rate (pr) also introduced in the employed bee phase which control the perturbation in the food positions explore by employed bees. The experiments show that the proposed strategy has better diversity and faster convergence than the basic ABC.

Keywords: Swarm intelligence, Artificial Bee Colony, Structured swarm.

1. INTRODUCTION

Swarm intelligence is a subset of artificial intelligence that studies about the social behavior and emergent properties of complex system with social structure. Such type of system consists of simple interactive agents unionized in small societies or swarm. Although is no central control, the aggregated behavior of whole swarm exhibits quality of intelligence i.e. decision making capacities. The algorithms which have emerged in recent years includes ant colony optimization (ACO) [6], particle swarm optimization (PSO) [12], bacterial foraging optimization (BFO) [14], artificial bee colony optimization (ABC) [9] etc. This section provides brief introduction of swarm intelligence based algorithms and problem solved by the algorithms is reported. It also covers the literature review done to solve the problem efficiently. In section 1.1 brief introductions of ABC is given.

1.1 Artificial Bee Colony

The artificial bee colony (ABC) is new optimization algorithm which can be de-fined under swarm intelligence. Artificial bee colony algorithm is inspired by social behavior of natural honey bees. ABC is introduced by Karaboga in 2005[9]. With reference to ABC, the potential solutions are food sources of honey bees. The fitness is determined in terms of the quality (nectar amount) of the food source. The total numbers of bees in the colony are divided into three groups: Onlooker Bees, Employed Bees and Scout Bees. Numbers of employed bees or onlooker bees are equal to the food sources. Employed bees are associated with food sources while

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

onlooker bees are those bees that stay in the hive and use the information gathered from employed bees to decide the food source. Scout bee searches the new food sources randomly.

Similar to the other population-based algorithms, ABC is an iterative process.

ABC process requires cycles of four phases: Initialization phase, Employed bees phase, Onlooker bees phase and Scout bee phase. Each of the phase is explained as follows:

i. Initialization of the population

Initially, ABC generates a uniformly distributed initial population of SN solutions where each solution $x_i(i = 1, 2, ..., SN)$ is a D-dimensional vector. Here D is the number of variables in the optimization problem and x_i represent the i^{th} food source in the population. Each food source is generated as follows:

$$x_{ij} = x_{minj} + rand[0, 1](x_{maxj} - x_{minj})$$

Where x_{minj} and x_{maxj} are bounds of x_i in j^{th} direction and rand[0, 1] is a uniformly distributed random number in the range [0, 1].

ii. Employed bee phase

In employed bee phase, employed bees modify the current solution based on the information of individual experience and the fitness value of the new solution (nectar amount). If the fitness value of the new source is higher than that of the old source, the bee up dates her position with the new one and discards the old one. The position up date equation for i^{th} candidate in this phase is

$$v_{ij} = x_{ij} + \phi_{ij} (x_{ij} - x_{kj}) \qquad (1.2)$$

Where $k \in 1, 2, ..., SN$ and $j \in 1, 2, ..., D$ are randomly chosen indices. k must be different from i. ϕ_{ij} is a random number between [-1, 1]. Figure (1.1) shows the position update process in the Employed bee phase.

iii. Onlooker bee phase

After completion of the employed bees phase, the onlooker bees phase starts. In onlooker bees phase, all the employed bees share the new fitness information (nectar) of the new solutions (food sources) and their position information with the onlooker bees in the hive. Onlooker bees analyze the available information and select a solution with a probability, p_i, related to its fitness. The probability p_i may be calculated using following expression (there may be some other but must be a function of fitness):

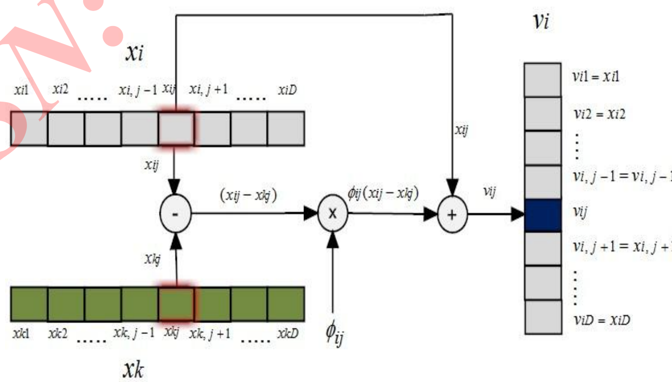

Figure 1.1: Position updation in employee bee phase

$$\frac{fiti}{\sum_{i=0}^{SN} fiti} \qquad (1.3)$$

Where fit_i the fitness is value of the solution i. As in the case of the employed bee, she produces a modification on the position in her memory and checks the fitness of the candidate source. If the fitness is higher than that of the previous one, the bee memorizes the new position and forgets the old one.

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

iv. Scout bees phase

If the position of a food source is not up dated up to predetermined number of cycles, then the food source is assumed to be abandoned and scout bees phase starts. In this phase the bee associated with the abandoned food source becomes scout bee and the food source is replaced by a randomly chosen food source within the search space. In ABC, predetermined number of cycles is a crucial control parameter which is called *limit* for abandonment. Assume that the abandoned source is x_i. The scout bee replaces this food source by a randomly chosen food source which is generated as follows:

$$x_{ij} = x_{minj} + rand[0, 1](x_{maxj} - x_{minj}), \; for\ j \in 1, 2, ..., D \quad (1.4)$$

2. LITERATURE REVIEW

2.1 Related Work

Artificial Bee Colony (ABC) algorithm is established by Karaboga in 2005 [9]. Since its inception, a lot of research has been carried out to make ABC more and more efficient and to apply ABC for different types of problems. The whole performance of the ABC algorithm has been compared with genetic algorithm (GA) [8], differential evolution, particle swarm inspired evolutionary algorithm (PS-EA) [11], evolutionary algorithm (EA) and PSO. PSO, ABC and DE algorithms were studied for measuring the effect of search space scaling in [5] .In order to get rid of the drawbacks of basic ABC, researchers have improved ABC in many ways.

Qingxian and Haijun [7] in 2008 proposed a modification in the initialization scheme by making the initial group symmetrical, and for selection instead of roulette wheel selection, Boltzmann selection mechanism was employed for improvement in the convergence ability of the ABC algorithm.

To improve the exploitation capacity of the onlooker bee stage, Tsai et al. in 2009 introduced the concept of Newtonian law of universal gravitation in the onlooker bee phase of the basic ABC algorithm in which onlookers are selected based on a roulette wheel (Interactive ABC, IABC) [14].

A modified version of the Artificial Bee Colony algorithm are introduced and applied for efficiently solving real-parameter optimization problems by Bahriye Akay and Dervis Karaboga in 2010[1] by applying two search parameters such as perturbation frequency and magnitude of the perturbation.

G. Zhu and S. Kwong [15] proposed an improved ABC algorithm called gbest guided ABC (GABC) algorithm by using the information of global best (gbest) solution into the solution search equation of ABC to improve the exploitation.

In 2010, Turkay Derelia and Gulesin Sena Das [5] proposed a hybrid bee(s) algorithm for solving container loading problems. In the proposed algorithm, a bee(s) algorithm is hybridized with the heuristic filling procedure for the solution of container loading problems.

In [10], Karaboga presented an extended version of ABC for constrained optimization problems. He applied it to train neural networks, to medical pattern classification and clustering problems [4] and to solve TSP problems.

Bilal Alatas in 2010 [2] proposed new modified ABC algorithms that use chaotic maps to improve the convergence characteristics and to prevent the ABC to get stuck on local optima. For this chaotic number generators has been used each time a random number is needed by the original ABC algorithm.

3. OBJECTIVE AND MOTIVATION

This chapter describes the objective of research and methodology adopted. Section 3.1 describes the objective of

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

research, section 3.2 provides the motivation for research and section 3.3 describes the methodology designed in solving the problem.

3.1 Objective

Swarm intelligence based algorithms have been gaining much popularity in re-cent years due to the fact that real world optimization problems have become increasingly large, complex and dynamic. The size and complexity of the problems nowadays require the development of methods and solutions whose efficiency is measured by their ability to find acceptable results within a reasonable amount of time, rather than an ability to guarantee the optimal solution. The main objective of our research is:

- To study the behavior of different swarm intelligence based algorithms.
- To check whether modification can be done on algorithm by tuning of control parameter, hybridizing two algorithms or introducing new control parameter.

3.2 Motivation

The exploration and exploitation are very important phenomenon for the population based optimization algorithms, such as DE, PSO, ABC, and so on. It is clear from the solution search equation of the ABC that the new food position is generated by directing the old one towards a randomly selected food position's from the swarm. However, in this process there is equal chance to skip the global minima, to get a good food solution and to get a bad one. Further, the solution search equation is significantly dominated by a coefficient ϕ_{ij} which is a uniform random number in $[-1, 1]$. Therefore, the ϕ_{ij} improves the exploration at the cost of exploitation. Hence, the solution search equation is better at exploration but poor at exploitation.

To set a trade-off between exploration and exploitation capability of ABC, the search capability of each bee (onlooker and employed) is guided by a local best food solution which is the solution having best fitness in the local subgroup. The updated solution search equation is shown below:

$$v_{ij} = x_{ij} + \phi_{ij} (x_{ij} - x_{kj}) + U(0, 1)(L_j - x_{kj})$$

Here, L_j is the j^{th} dimension of local best food solution and $U(0, 1)$ is a uniform random number between 0 and 1 and remaining symbols have their usual meanings. Further, to implement the proposed strategy, the swarm is dynamically divided into subgroups.

In the original ABC, all the bees are influenced from whole swarm; .therefore, there is a chance to get stuck in a local minima (stagnation). Therefore, to maintain better diversity in the search process, the search capability of each bee (onlooker and employed) is guided by a set of bees (subgroup). Hence the whole swarm is divided into subgroups of smaller size in both the phases (onlooker and employed bees) of the algorithm. Now bees search the food positions by learning within the subgroup i.e. every bee now influence by the social behavior of its own group bees. This phenomena improves local search capability i.e. exploitation in the search space. It is described in equation (3.1) that in the proposed strategy, randomly selected food position x_{kj} will be from the local subgroup of the solution space and L_j will be the local best food position of that subgroup. Next, each subgroup search independently in the whole search space and size of the subgroups changes dynamically, hence in the solution search process, exploration is achieved. So, it is clear from discussion that a good diversity and fast convergence can be achieved by the proposed strategy.

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

REFERENCES

[1] B. Akay and D. Karaboga. A modified artificial bee colony algorithm for real-parameter optimization. *Information Sciences*, 2010.

[2] B. Alatas. Chaotic bee colony algorithms for global numerical optimization. *Expert Systems with Applications*, 37(8):5682–5687, 2010.

[3] B. Akay D. Karaboga. Effect of region scaling on the initialization of particle swarm optimization differential evolution and artificial bee colony algorithms on multimodal high dimensional problems. In *International Conference on Multivariate Statistical Modelling and High Dimensional Data Mining (Kay-seri, TURKEY)*, June 1923, 2008.

[4] B. Akay D. Karaboga, C. Ozturk. Training neural networks with abc opti-mization algorithm on medical pattern classification. *International Confer-ence on Multivariate Statistical Modelling and High Dimensional Data Min-ing (Kayseri, TURKEY)*, June 1923, 2008.

[5] T. Derelia and G.S. Dasb. A hybrid'bee(s) algorithm'for solving container loading problems. *Applied Soft Computing*, 2010.

[6] M. Dorigo and T. Stutzle. *Ant colony optimization*. the MIT Press, 2004.

[7] D. Haijun F. Qingxian. Bee colony algorithm for the function optimization. *Science Paper Online*, August 2008.

[8] D.E. Goldberg. Genetic algorithms in search, optimization, and machine learning. 1989.

[9] D. Karaboga. An idea based on honey bee swarm for numerical optimization. *Techn. Rep. TR06, Erciyes Univ. Press, Erciyes*, 2005.

[10] D. Karaboga and B. Basturk. Artificial bee colony (abc) optimization algorithm for solving constrained optimization problems. *Foundations of Fuzzy Logic and Soft Computing*, pages 789–798, 2007.

[11] D. Karaboga and B. Basturk. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (abc) algorithm. *Journal of Global Optimization*, 39(3):459–471, 2007.

[12] J. Kennedy and R. Eberhart. Particle swarm optimization. In *Neural Networks,1995. Proceedings., IEEE International Conference on*, volume 4, pages 1942–1948. IEEE, 1995.

[13] K.M. Passino. Biomimicry of bacterial foraging for distributed optimization and control. *Control Systems Magazine, IEEE*, 22(3):52–67, 2002.

[14] P.W. Tsai, J.S. Pan, B.Y. Liao, and S.C. Chu. Enhanced artificial bee colony optimization. *International Journal of Innovative Computing, Information and Control*, 5(12), 2009.

[15] Guopu Zhu and Sam Kwong. Gbest-guided artificial bee colony algorithm for numerical function optimization. *Applied Mathematics and Computation*, 217(1):3166–3173, 2010.