# A NEW HYBRIDIZED APPROACH OF PSO & ABC FOR OPTIMIZATION

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***ABSTRACT***

This article presents a hybrid evolutionary algorithm (PSABC) based on Artificial Bee Colony (ABC) and particle swarm optimization (PSO). Both of the algorithms are co-operative, population-based global search swarm intelligence met heuristics. The core of this algorithm is using PSO to optimize the fitness value of population in ABC. For Evaluation purpose, the proposed algorithm is tested on number of standard optimization functions. The results of experimentations have shown the superiority of proposed algorithm over standard PSO and ABC.

***KEY WORDS***

Swarm Intelligence, Artificial Bee Colony, Particle Swarm Optimization

## 1 INTRODUCTION

Recently there has been increased interest in swarm intelligence applied to changing optimization problems. Swarm intelligence models the population of interacting agents or swarms that are able to self organize [1][2]. Ant colonies, bird flocking, animal herding, bacterial molding and bees swarming is a typical example of a swarm system. In Bee Colony model which is an evolutionary and population based 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[3].

Particle swarm optimization is a population-based method. PSO starts with a random population of particles. Each particle of the population tries to move toward the points of search space in which the best experience of the particle itself and also the best experience of the population occurred[4].

The rest of paper is organized as follow. Section 2, 3 introduce ABC and PSO algorithms. In order to improve the performance of ABC algorithm, PSABC algorithm is proposed in section 4. The simulation results obtained are presented and discussed in section 5. Finally, the conclusion is in section 6.

## 2 THE ABC ALGORITHM

The Artificial Bee Colony (ABC) algorithm uses a colony of artificial bees. The bees are classified into three types: Employed bees, Onlooker bees, and Scout bees. Each employed bee is associated with a food source, which it exploits currently. A bee waiting in the hive to choose a food source is an onlooker bee. The employed bees share information about the food sources with onlooker bees in the dance area. on the other hand, A scout bee, carries out a random search to discover new food sources.[5] The main steps of the algorithm are given below. At the first step, the algorithm generates a randomly distributed initial population contains NS solutions. Where NS is the number of food sources and it is equal to the number of employed bees. Each solution xi (i=1, 2,...,Ns) is a ndimensional vector. In ABC, the fitness function is defined as follows:

$$fit_i = \begin{cases} \frac{1}{1+f_i} & f_i \geq 0 \\ 1 + abs(f_i) & f_i < 0 \end{cases} \qquad (1)$$

where $f_i$ is the objective function value of solution $i$, $fit_i$ is the fitness value of solution $i$ after transformation. An onlooker bee chooses a food source depending on the probability value i p associated with that food source,

$$p_i = {fit_i}\Big/{\sum_{j=1}^{Ns} fit_i} \qquad (2)$$

A candidate solution vi from the old solution xi can be generated as

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}) \qquad (3)$$

where k $\in${1, 2, NS} and j $\in${1, 2, n} are randomly chosen indexes; k has to be different from i; ij is a random number in the range [-1, 1].

After each candidate source position is produced and evaluated by the artificial bee, its performance is compared with that of its old one. If the new food source has equal or better quality than the old source, the old one is replaced by the new one. Otherwise, the old one is retained. If a position cannot be improved further through a predetermined number limit (limited cycles), then that food source is assumed to be abandoned. The corresponding employed bee becomes a scout. The abandoned position will be replaced with a new food source found by the scout. Assume that the abandoned source is xi, and then the scout discovers a new food source as

$$x_{ij} = l_j + rand(0,1)(u_j - l_j) \qquad (4)$$

cause autobody panels emphasis curved surface whole artistic effects, measurement accuracy is not the first problem considered in the course of the measuring car body, but trying to make the development time shorter [4]. where lj and uj are lower and upper bounds of the variable xij[6].

## 3 PARTICLE SWARM OPTIMIZATION

The particle swarm optimization (PSO) algorithm is introduced by Kennedy and Eberhart based on the social behavior metaphor. In PSO a potential solution for a problem is considered as a bird without quality and volume, which is called a particle, flying through a D-dimensional space, adjusting its position in search space according to its own experience and its neighbors. In PSO, the ith particle is represented by its position vector pi in the D-dimensional space and its velocity vector vi. In each time step t, the particles calculate their new velocity then update their position according to eq. (5) and eq. (6) respectively.

$$v_i(t+1) = v_i(t) + c_1 r_1 \left(p_i^{best} - p_i(t)\right) + c_2 r_2 (lbest_i - p_i(t)) \quad (5)$$

$$p_1(t+1) = p_1(t) + v_1(t+1) \quad (6)$$

Where best i p is the best personal position of particle i which has been visited during the lifetime of the particle. lbesti is the local best position that is the best position of all neighboring particles of particle i. c1 and c2 are positive acceleration constants used to scale the contribution of cognitive and social components respectively. r1 and r2 are uniform random variables in range [0, 1] [7] [8].

## 4 PSABC ALGORITHM

Detailed of methode by broposed PSABC presented in this section.

In Initilization, constant and variable are determined. The colony size, the number of bees, the learning constant, including c1, c2 and x in PSO, should be assigned in advanced. In PSABC, ABC and PSO both work with same population. In this algorithm the population is randomly generated. These may be regarded as bee colony in term of ABC, or as particles in terms of PSO. In each cycle, after the fitness of all bees in same population is calculated, the employed bees are mark and we enhance them by PSO. By performing PSO solution on the employed bee, we increase the search ability.

## 5 EXPERIMENTS AND RESULTS

The proposed algorithm was tested on four classical benchmark functions as in [8]. The functions used along with their parameter ranges and have been listed in Table I. The size of the bee colony was chosen as 100 with 50% employed bees and 50% onlooker bees (SN = 50).

Tab.1 Test Function

| Function | Equation | Range |
|---|---|---|
| Sphere | $f_1(\mathrm{x}) = \sum_{\mathrm{i}=1}^{\mathrm{D}} \mathrm{x}_\mathrm{i}^2$ | $[-100\ 100]^n$ |
| Rosenbrock | $f_2(\mathrm{x}) = \sum_{\mathrm{i}=1}^{\mathrm{D}} \left(100\left(\mathrm{x}_{\mathrm{i}+1} - \mathrm{x}_\mathrm{i}^2\right)^2 + (\mathrm{x}_\mathrm{i} - 1)^2\right)$ | $[-30\ 30]^n$ |
| Rastrigin | $f_5(\mathrm{x}) = \sum_{\mathrm{i}=1}^{\mathrm{D}} \left(\mathrm{x}_\mathrm{i}^2 - 10\cos(2\pi \mathrm{x}_\mathrm{i}) + 10\right)$ | $[-5.12\ 5.12]^n$ |
| Ackley | $f_3(\mathrm{x}) = 20 + \mathrm{e} - 20\mathrm{e}^{\left(-0.2\sqrt{\frac{1}{\mathrm{D}}\sum_{\mathrm{i}=1}^{\mathrm{D}} \mathrm{x}_\mathrm{i}^2}\right)} - \mathrm{e}^{\frac{1}{\mathrm{D}}\sum_{\mathrm{i}=1}^{\mathrm{D}} \cos(2\pi \mathrm{x}_\mathrm{i})}$ | $[-32\ 32]^n$ |

A maximum of one scout bee is produced per cycle. The dimension is 10, 20, 30 for all functions and limit = SN * D. The ABC algorithm was run for 500 iterations for functions. The mean and the best values of several algorithms such as PSO, PSO-I.W [4], AFSA [10], ABC [2] and CLA [9] over 30 runs have been tabulated in [1]Tables 2-5.

Tab.2 Simulation Results of Rastrigin Function

| | | Dimension | | |
|---|---|---|---|---|
| | | 10 | 20 | 30 |
| PSO | Best | 4.97 | 10.05 | 28.49 |
| | Mean | 10.14 | 28.21 | 57.1 |
| PSO-I.W | Best | 3.65 | 10.99 | 24.25 |

| | | | | |
|---|---|---|---|---|
| | Mean | 8.69 | 28.93 | 34.16 |
| AFSA | Best | 10.179 | 20.548 | 51.183 |
| | Mean | 81.841 | 113.198 | 182.507 |
| ABC | Best | 2.36E-15 | 2.67E-06 | 5.04 |
| | Mean | 0.65 | 6.58 | 19.04 |
| CLA | Best | 1.36E-16 | 1.12E-06 | 0.058 |
| | Mean | 0.019 | 1.12E-06 | 0.23 |
| PSABC | Best | 1.42E-15 | 1.44E-06 | 3.01408 |
| | Mean | 3.97E-11 | 0.077 | 7.057844 |

Tab.3 Simulation Results of Rosenborke Function

| | | Dimension | | |
|---|---|---|---|---|
| | | 10 | 20 | 30 |
| PSO | Best | 352.86 | 31674.26 | 89 |
| | Mean | 14.39 | 5.86E+03 | 29.15 |
| PSO-I.W | Best | 0.43 | 14.72 | 29.15 |
| | Mean | 11.33 | 35.24 | 89 |
| AFSA | Best | 75.041 | 187.142 | 458.142 |
| | Mean | 336.906 | 72.891 | 108.281 |
| ABC | Best | 4.04 | 9.46 | 274.2 |
| | Mean | 1.00E-04 | 0.0062 | 0.0205 |
| CLA | Best | 4.00E-02 | 0.63 | 15.88 |
| | Mean | 3.87E-06 | 1.39E-06 | 5.98E-04 |
| PSABC | Best | 7.31E-03 | 3.70E-03 | 0.032 |
| | Mean | 5.20E-06 | 4.00E-05 | 6.11E-03 |

Tab.4 Simulation Results of Sphere Function

| | | Dimension | | |
|---|---|---|---|---|
| | | 10 | 20 | 30 |
| PSO | Best | 0.009 | 6.90E-01 | 2.11 |
| | Mean | 0.33 | 9.21 | 15.08 |
| PSO-I.W | Best | 0.0004 | 0.008 | 0.02 |
| | Mean | 0.002 | 7.07 | 5.82 |
| AFSA | Best | 0.0069 | 0.0085 | 0.0594 |
| | Mean | 0.0201 | 0.0245 | 0.0938 |
| ABC | Best | 5.15E-14 | 3.60E-07 | 1.07E-05 |
| | Mean | 4.44E-05 | 68.862 | 836.142 |
| CLA | Best | 1.25E-16 | 4.53E-09 | 4.30E-07 |
| | Mean | 5.79E-04 | 0.85 | 10.12 |
| PSABC | Best | 7.84E-16 | 6.52E-10 | 1.66E-07 |
| | Mean | 1.56E-16 | 1.23E-08 | 7.99E-06 |

Tab.5 Simulation Results of Ackley Function

| | | Dimension | | |
|---|---|---|---|---|
| | | 10 | 20 | 30 |
| PSO | Best | 0.59 | 4.32 | 7.46 |
| | Mean | 2.5 | 6.09 | 9.11 |
| PSO-I.W | Best | 0.08 | 3.76 | 6.54 |
| | Mean | 2.49 | 5.36 | 8.34 |
| AFSA | Best | 0.1698 | 0.4916 | 29.024 |

| | | | | |
|---|---|---|---|---|
| | Mean | 11.659 | 24.896 | 46518 |
| ABC | Best | 3.38E-10 | 5.72E-04 | 0.029 |
| | Mean | 1.11E-07 | 0.32 | 1.88 |
| CLA | Best | 4.32E-10 | 2.56E-05 | 2.55E-05 |
| | Mean | 1.24E-04 | 0.014 | 6.50E-05 |
| PSABC | Best | 1.02E-11 | 1.16E-08 | 4.78E-07 |
| | Mean | 1.35E-08 | 1.26E-03 | 1.10E-03 |

## 6. SUMMARIES

In this work, a new optimization algorithm based on the intelligent behaviour of honey bee swarm and PSO has been described. The new swarm algorithm is very simple and very flexible when compared to the existing swarm based algorithms. It is also very robust, at least for the test problems considered in this work. From the simulation results, it is concluded that the proposed algorithm

can be used for solving unimodal and multi-modal numerical optimization problems. In this work, the algorithm was tested on a very limited set of test problems.

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