

COMPARATIVE STUDY OF PARTICLE SWARM OPTIMIZATION AND ARTIFICIAL BEE COLONY ALGORITHMS

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ABSTRACT

In this work greedy comparison between particle swarm optimization and artificial bee colony algorithms was made using different test functions. Each algorithm was explained in detail, and the mathematical model behind the algorithms has been presented. It is found that particle swarm optimization is better than artificial bee colony and for a specific test function, artificial bee had failed to find a feasible solution.

1. INTRODUCTION

PSO is a swarm intelligence optimization algorithm; it belongs to a class of optimization algorithms called meta-heuristics. PSO mimics the social behavior of animals like fish and birds, and it is a simple, powerful optimization algorithm. It was successfully applied to enormous applications in different fields of science and engineering like machine learning, image processing, data mining, robotics and many others. Initially, PSO is introduced in 1995 by Russell Eberhart and James Kennedy [1]. They were working to develop a model describing the social behavior of animals like a flock of birds and school of fishes. Since 1995, though its simplicity, PSO has become one of the most useful and most popular algorithms to solve various optimization problems in various fields. The key point in this intelligence is the cooperation among those agents. Definitely, the level of the swarm intelligence cannot be reached by an individual unless it cooperates with another party [2]. In 2005, [3] has introduced a swarm intelligence optimization algorithm called artificial bee colony ABC. It is a metaheuristic algorithm that can be used to solve multi-dimensional optimization problems effectively. It mimics the foraging behavior of the honey bee colony and based on the model proposed by [4]. Artificial bee colony, states that there is a population of bees (agents) searching for the richer food source (best solution) in the neighborhood of the hive (search space). Every agent is a candidate solution and associated with only one particular solution in the search space.

2. PSO ALGORITHM

Consider Figure 1 which is the mathematical model behind the PSO

By analogy, we can refer to the members of the swarm and the swarm itself as particles and population respectively, and every particle is a candidate solution to the optimization problem that should be solved. The search space limits all the possible solutions to a problem, and the particles have to reach to the best position (the best solution for the optimization problem) in the space. The position and velocity of a specific particle are denoted by

$$x_k(t) \in x$$

$v_k(t) \in x$ where k is the index of the particle in the swarm and x is the search space while t is a discrete time step and it shows the iteration number of the algorithm. The velocity and position vectors are located in the same space with the same dimensionality. Consider the scheme shown in Figure 1 which illustrates a simple mathematical model describing PSO. Where $x_k(t)$ is the current location of the particle and it has to move to the new position $x_k(t+1)$. Each particle has its own experience and its own memory about the best position where it was, we shall call it personal best of the k^{th} particle and denoted by $p_k(t)$. The particle moves from its position with a velocity in the direction of $v_k(t)$. These particles are not alone, they are communicating and interacting with each other and share their personal experience so they learn and decide what is the best experience among all the experiences of the other party, we shall call it global best and denoted by $G(t)$. The following quantities can be extracted from Figure 1:

The value of the vector connecting the current location and the personal best is:

$$p_x = p_k(t) - x_k(t) \quad (1)$$

Also, the value of the vector connecting the current location to the global best is:

$$g_x = G(t) - x_k(t) \quad (2)$$

The particle has to move the new position; this movement can be expressed as:

$$x_k(t+1) = x_k(t) + v_k(t+1) \quad (3)$$

$$v_k(t+1) = w * v_k(t) + C_1(p_k(t) - x_k(t)) + C_2(G(t) - x_k(t)) \quad (4)$$

In equation (4), the vector $v_k(t+1)$ is the summation of the three sub-movements m_1 , m_2 and m_3 where they are the movement of the particle along the vectors $v_k(t)$, p_x and g_x respectively, so we can write:

$$v_k(t+1) = m_1 + m_2 + m_3 \quad (5)$$

where

$$m_1 = w * v_k(t) \quad (6)$$

$$m_2 = C_1 p_x = C_1 (p_k(t) - x_k(t)) \quad (7)$$

$$m_3 = C_2 g_x = C_2 (G(t) - x_k(t)) \quad (8)$$

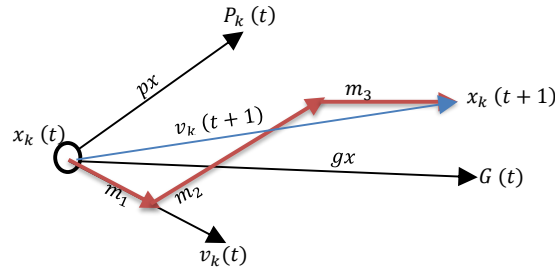


Figure 1. Schematic diagram representing the mathematical model of PSO

Equations (3) and (4) completely describe the mathematical model of PSO. However, these equations are simple mathematical model behind the standard PSO, and some situations are necessary to complete the equations. The standard PSO is as follows

$$x_{kj}(t+1) = x_{kj}(t) + v_{kj}(t+1) \quad (9)$$

$$v_{kj}(t+1) = w * v_{kj}(t) + r_1 C_1 (p_{kj}(t) - x_{kj}(t)) + r_2 C_2 (G_j(t) - x_{kj}(t)) \quad (10)$$

$v_{kj}(t+1)$: denote the velocity of particle k in time step $(t+1)$ of the j^{th} component for this velocity

r_1, r_2 : a random number uniformly distributed in the range 0 to 1

C_1, C_2 : acceleration coefficient

$w * v_{kj}(t)$: inertia term

w : inertia coefficient

$r_1 C_1 (p_{kj}(t) - x_{kj}(t))$: cognitive component

$r_2 C_2 (G_j(t) - x_{kj}(t))$: social component

Equations (9) and (10) are the two rules that should be followed by all particles in the swarm, and that is the exact meaning of the swarm intelligence. By defining these rules on every iteration of PSO, velocity and position of each particle are updated according to this simple mechanism.

3. ARTIFICIAL BEE COLONY

The general scheme of the algorithm is as follows:

Scout Bees Phase (Initialization)

Repeat

Employed bees' section

Onlooker bees' section

Scout bees' section

Memorize the best solution in the current trail

Until (stop condition reached; maximum numbers of cycles)

Each section of the algorithm has its own low-level structure and they affect the global level by interactions between them. Initially, all bees are scouts and search for new solutions randomly.

Assume x is a vector of random solutions that initially returned by scout bees.

$$x = (x_1, x_2, x_i, \dots, x_{n-1}, x_n) \quad (11)$$

where $n \in R^n$, $i=1 \dots n$

3.1 Employed bees' section

Employed bees exploit the food source and return information about it and they abandon the exhausted one. At ABC we have to do that randomly.

[5] has proposed the following formula:

$$v_i = x_i + \phi_i(x_i - x_k) \quad (12)$$

Where v_i is the new solution vector, ϕ_i is a random number in the period $[-1,1]$. k is random number representing different random order in the solution vector.

3.2 Onlooker bees' section

Onlooker bees use probability which is a function of fitness value to select the best solution. Roulette wheel selection method [6] which is fitness value based selection technique. The probability of a solution (P_i) should be:

$$P_i = \frac{f_i}{\sum_{i=1}^{pop} f_i} \quad (13)$$

$$f_i = \begin{cases} \frac{1}{1+O_i} & O_i \geq 0 \\ 1+abs(O_i) & O_i < 0 \end{cases} \quad (14)$$

where f_i is the fitness value of the objective function O_i .

3.3 Scout bees' section

At the beginning of the algorithm, all the bees are scouts and later convert to employ or onlooker during run time. The employed bees whose position (solution) does not change after a specific time of trails have to abandon their position and convert to scouts. Abandonment criterion which is called limit control is very important to jump from local minimum and continue to search for the global minimum of the optimization problem.

4. TESTS FUNCTIONS

Different test functions were used to make a comparison between particle swarm optimization and artificial bee colony. Table 1 illustrates a comparison between the two algorithms over different five test function [7]. By observing the standard deviation for the costs and mean cost values of the population, it is clear, that the advantage is at the PSO algorithm. Also, it is found that the ABC algorithm fails to converge to a solution when using the Schwefel's function.

Table 1. PSO versus ABC over different test functions

Test function	global	algorithm	best	mean	St.dev
Sphere	0	PSO	0	0.0030	0.0365
		ABC	0	0.0112	0.0763
Rosenbrock's valley	0	PSO	0	0.0166	0.0621
		ABC	0	0.0252	0.0453
Rastrigin's function	0	PSO	0	0.1556	1.0164
		ABC	0	0.3091	1.5653
Schwefel's function	-837.9658	PSO	-719.5274	-717.7633	12.9889
		ABC	-7.86*10 ⁸³	-6.89*10 ⁸¹	6.06*10 ⁸²
Griewangk's function	0	PSO	0.0049	0.0347	0.1426
		ABC	0.0025	0.0592	0.1973

5. CONCLUSION

Optimization techniques play an important role finding the best solution from many alternatives. A great number of optimization techniques are available. Nowadays

the metaheuristic algorithms are popular. The Particle swarm and the Bee colony algorithms have been selected. Both use the swarm intelligence. In our comparisons we have found the better applicability of the Particle swarm algorithm.

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