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Comparison of Swarm Intelligence Algorithms for High Dimensional Optimization Problems

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ABSTRACT

High dimensional optimization considers being one of the most challenges that face the algorithms for finding an optimal solution for real-world problems. These problems have been appeared in diverse practical fields including business and industries. Within a huge number of algorithms, selecting one algorithm among others for solving the high dimensional optimization problem is not an easily accomplished task. This paper presents a comprehensive study of two swarm intelligence based algorithms: 1-particle swarm optimization (PSO), 2-cuckoo search (CS).The two algorithms are analyzed and compared for problems consisting of high dimensions in respect of solution accuracy, and runtime performance by various classes of benchmark functions.

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1. INTRODUCTION

Optimization is a procedure of adjusting system characteristics to make it works effectively under some constraints or conditions. Optimization algorithms have been utilized in the various fields to solve the real-world optimization problem, and these algorithms have been designed to satisfy the requirement of an applied system [1]. For each optimization problem, there are set of possible solutions called solution scope [1]. The achievable solution founded by the algorithm may consider as a global optimum if it is the only better solution among other feasible solutions. Computing global optimal for the high dimensional optimization problem is complex [2], and considers being one of the most challenges facing the optimization algorithms. Since optimization problems appear in diverse fields including engineering, manufacture and the economic system, there is a necessary need for an efficient algorithm that could solve the high dimensional problem successfully [3].

Two main types of global optimization methods are founded in literature: deterministic and probabilistic [4]. Deterministic algorithms deal with the problem by making a clear assumption of it and exploring the search space in a suitable way to achieve a fixed solution within an acceptable amount of time [4]. These algorithms could not use in such problems that have large search area such as high dimensional optimization problem. In addition, due to time constraint, these methods have a less capability to explore the large search space [5]. However, probabilistic algorithms such as metaheuristic algorithms have shown advanced in the high dimensional optimization [6]. Metaheuristic algorithms are taken its essences from nature. Two characteristics have formed these algorithms: exploration and exploitation [6, 7]. Exploration is seeking the search space, while exploiting is utilizing the visited area to examine that the global solution within the area [7]. Consequently, metaheuristic algorithms have a chance to achieve the global optimum solution [8, 9]. Many fields including computer science, Artificial Intelligence, machine learning, and data mining have used the metaheuristic algorithms in their optimization procedure [8]. Although the metaheuristic algorithms have the same concept of taking their idea from nature, these algorithms come with different search mechanisms [9], and various inspired sources [7]. For instance, algorithms such as genetic algorithms (GA), and differential evolution (DE) are bio-inspired based algorithm while particle swarm optimization (PSO), Ant Colony Optimization (ACO), and cuckoo search (CS) are swarm intelligence-based algorithm [10]. In this study, we have chosen swarm intelligence algorithms to deal with high dimensional optimization problem. There are more than one hundred heuristic algorithms and many of them could solve different type of optimization problems effectively [5]. Within the huge number of algorithms selecting one algorithm among others to apply it in a specific domain to solve the high dimensional problem is not an easily accomplished task. For that, the paper aims to determine the algorithm that could resolve the high dimensional problem properly. This article is focusing on analyzing, and comparing in details particle swarm optimization (PSO) and cuckoo search (CS) in respect of solution accuracy and runtime performance on standard benchmark functions. The organization of this paper is shown as follow: Section II provides the optimization problem description. Section III shows a review of (PSO), and (CS). The standard function using in experiments are in section IV, while the results and conclusion are presented in section V and VI respectively.

2. HIGH DIMENSIONAL OPTIMIZATION PROBLEM

High dimensional optimization has two main issues one is that within the increase of dimensions number, the number of possible solutions is grown extensively [1, 3]. And the other is that the search space extended exponentially [1, 3]. These two issues make the algorithm face a difficulty to achieve an optimal solution at the appropriate time [11]. Although optimization methods have been utilized in the various large-scale space problems including electronic systems designing, enormous resources scheduling, an effective solution for problems involving high dimensions is highly required [11]. With the rapid evolution and increases of data among various fields, the need to test an existing algorithm to find the suitable method that cope the high dimensional optimization problems is crucial.

2.1 Problem Formulation

Many crucial fields including engineering, medicine, and economics rely on optimization mechanism to achieve their requirements. The optimization of the problems fields could be represented using mathematical functions to be solved by computational methods [12]. Optimization problem expressed by:

1) The cost function objective function or represents the goals of optimization either minimize or maximize.

$$f : X \mapsto Y \tag{1}$$

Where Y should belong to the real number $Y \subseteq R$, X represented the parameters or dimensions of the problem, and R is represented the search scope

2) The dimensions or variables of the problem $(x_1, x_2, ..., x_n)$.

3) The constraints, which determine the boundary dimensions of a particular problem.

In this study, the cost function is indicated by the fitness or quality of variables for a minimization problem.

$$\text{Minimize } f(x),\ x_i = (x_1, x_2, ..., x_n) \tag{2}$$

x_i is considered as a global solution to a given problem if the solution is better than any other solutions.

3. INTELLIGENCE METHODS

Swarm means a group of birds, ants or bees live in colonies [13, 14] in which the parts of the group communicate for varies tasks such as building a new nest or searching for food. Swarm intelligence algorithms are widely used for optimization problem among other algorithms; for instance, particle swarm optimization and cuckoo search are applied in science and engineering, and these algorithms have the ability to tackle the varies types of optimization problems [6].

3.1. Particle Swarm Optimization

Eberhart and Kennedy in 1995 proposed a swarm based intelligence algorithm named Particle swarm optimization (PSO) [15]. Particle swarm optimization functionality relay on the particles.Two characteristics: position and velocity belong to every single particle. The particles have the tow best position: personal (Pbest) and global (Gbest) respect to the whole group making the particle learn from its experience as well as from the whole group for searching an optimized solution. These poisons are updating based on the fitness value comparison between the current and the new position. Until the swarm finds the desired solution this process has been replicated many times. Three vectors are using for identifying particle in the search scope: position $X_i(t)$, velocity, $V_i(t)$, and personal best position P_{best} .In addition, its movement determined by P_{best} and G_{best}. PSO velocity and position formula are presented in equation 3,4 receptively.

$$V_i(t+1) = V_i(t) + c_1 * r_1 * (P_{best} - X_i(t)) + c_2 * r_2 * (G_{best} - X_i(t) \tag{3}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{4}$$

Where, r_1, r_2 random numbers with values between (0,1) while c_1, and c_2 are learning factors. PSO utilizes these factors to control the updating process of particle velocity and position. These two parameters are used to control the velocity and position of the particle.

Particle swarm optimization has appealed many researchers over other algorithms. The algorithm is simple to implement and has less number of parameters [16]. On the other hand, it has some drawbacks that preventing the algorithm from effectively working on some optimization problem. The researchers solved this problem by some modification on the basic version. One of this modification is proposed by Shi and Eberhart in 1998, they introduced the Inertia Weight equals to 1 to control exploration and exploitation in search space [17], and the velocity equation is altered to (5).

$$V_i(t+1) = w * V_i(t) + c_1 * r_1 * (P_{best} - X_i(t)) + c_2 * r_2 * (G_{best} - X_i(t)) \tag{5}$$

Because of the importance of the inertia weight on the PSO performance, it has been well studied in the literature [18]. In this study, the inertia weight is equal to w=0.7298 [19]. The Pseudocode of particle swarm optimization is as follows:

For individual particle(i)
Initialize particle velocity
Initialize particle position
End
Do
For i =1 to population size
Evaluate the fitness value
If the current fitness value is better than the particle best value (P_{best})
assign current value to particle best value (P_{best})
end
For each particle
Find particle with the best fitness among all particles as (G_{best})
Update particle velocity according to equation (3)
Update particle position according to equation (4)
End
While maximum iteration is not reached

3.2. Cuckoo Search

New based swarm intelligence algorithm named Cuckoo search(CS) has been announced in 2009 [20]. cuckoo search takes its concepts from the cuckoo bird which depend on other birds to brood its eggs. Cuckoo search has presented advantage performance over many optimization problems; additionally, a study has mentioned that this algorithm has an ability to find the global optimal [21]. CS has only two parameters to control its progress. That means it doesn't need to regulate the parameter values for specific problems. For that, CS seems to be more generic for variation number of optimization problems [20]. Cuckoo search follows these steps mimicking the cuckoo birds.

First, cuckoo birds select a random nest to put its eggs on it. Second, the nest with good merits will be transferred to the next production. Finally, the host birds have two choices either throw away the eggs or leave the nest to create a new one with the probability Pa $\in$ (0, 1). The algorithm implementation is performed based on the probability of using the new cuckoo solution [instead of the bad old solution.Lév y flight is invoked whenever there is new creating of the solution as shown in equation (6) and its step obtained by Lévy [20].

$$X_i(t+1) = X_i(t) + \alpha \oplus \text{Lévy}(\lambda) \tag{6}$$

Where α>0 and set to 1 in cuckoo search and λ is a parameter which determines the number of appearance throughout unit interval [21].

Based on steps above the CS procedure can summaries in the pseudocode:
Begin
Initialize population values of the host nest
Do
Generate new cuckoo solution using Levy flight and evaluate it
If the cuckoo eggs better than the host eggs
Replace the host eggs by cuckoo
End if
By detection fraction of (pa) as worst nest build new nest
Save the best solutions and grade them
Select the current best solution
While maximum iteration is not reached

4. RESEARCH METHOD

Standard benchmark functions have been presented to validate the new algorithm as well as a comparison between several algorithms [22, 23]. These functions have a various category such as unimodal, multimodal, hybrid and comparison function. Three standard test functions are considered in this study including Ackley function, Rosenbrock function, and Rastrigin function.

Ackley's function, has many local minima making the algorithm faces difficulty to escape them. It is a multimodal function [22]. The two-dimension form is presented in Figure 1 and the evaluated formula in equation (7).

$$f(x) = 20 + \exp(1) - 20\exp(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}) - \exp(\frac{1}{D}\sum_{i=1}^{D}\cos(2\prod x_i)) \tag{7}$$

Ackley's function, has global minimum $f(x^*) = 0$ at $x^* = (0,0,...,0)$ with this constraint $x_i \in [-5,5]$ for i=1,2, 3,..,D

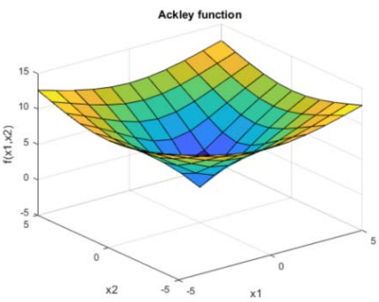

Figure 1. Ackley Function of Two Dimensions

The Rosenbrock Function is a unimodal function which algorithm could easily find the range of global minimum; however, reaching the optimal solution is difficult.

$$f(x) = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i^2)^2 + (x_i^2 - 1)^2] \quad (8)$$

Its global minimum $f(x^*) = 0$ at $x^* = (1,1,...,1)$ with this constraint $x_i \in [-5,5]$ where for=1,2, 3,..,D

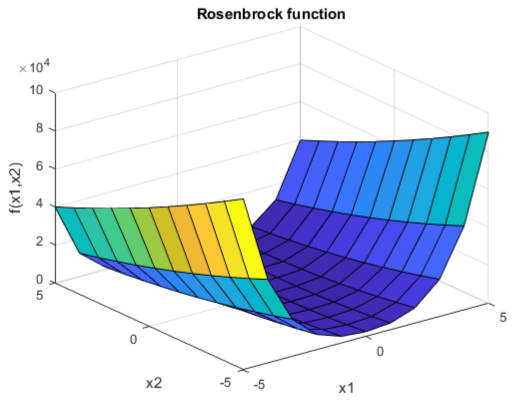

Figure 2. Rosenbrock Function fo of Two Dimensions

Rastrigin's function, which has many local minima and considers as a multimodal function. The two-dimension form is shown in Figure 3, and the formula of function evaluation in Equation 9.

.

$$f(x) = 10D + \sum_{i=1}^{D} [x_i^2 - 10\cos(2\prod x_i)] \quad (9)$$

Rastrigin's function has global minimum $f(x^*) = 0$ at $x^* = (0,0,...,0)$ with this constraint $x_i \in [-5.12, 5.12]$ for i=1,2, 3,...,D

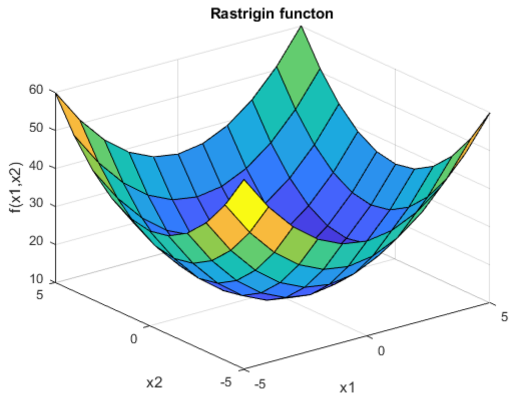

Figure 3. Rastrigin Function of Two Dimensions

In this study, these control parameters presented in the Table 1 are used for both algorithms in the experiment.

Table 1. Control Parameters

Algorithms	Parameters values
PSO	w =0.7298; $c_1 = c_2 = 2.05$
CS	N=25; P_a =0.25

5. RESULTS

Each of the two algorithms PSO and CS were tested on three test functions namely, Ackley, Rastrigin, and Rosenbrock for D=2,5,10,50,100 and 150. All implementation and analysis were performed in MATLAB. The two-algorithms had the same number of maximum iteration to perform a fair comparison [5]. The maximum iteration equaled to 3000.The comparison is based on solution accuracy, and runtime performance.

5.1. Solution Accuracy

It can be noticed from the presented results in figures 4,5, and 6 that the two algorithms PSO and CS had almost comparable results, i:e. $f(x^*) = 0$ for D ≤ 10 in all three functions. For the functions that have D≥ 50 CS achieved reasonable fitness value better than PSO. It can be concluded that CS, has more appropriate accuracy for problems containing dimensions up to 150 comparing with PSO.

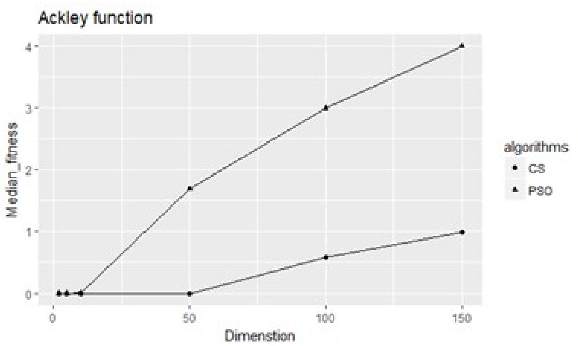

Figure 4. Accuracy Comparing of CS and PSO on Ackley Function

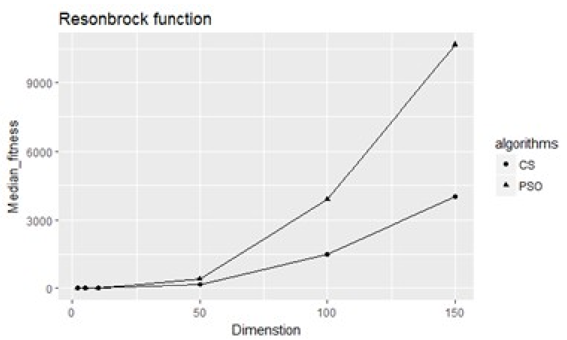

Figure 5. Accuracy Comparing of CS and PSO on Rosenbrock Function

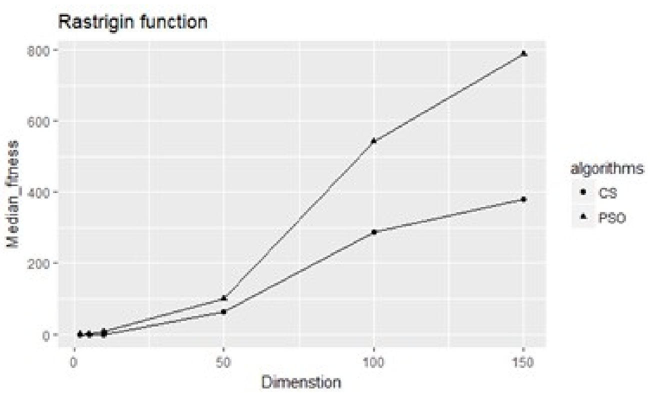

Figure 6. Accuracy Comparing of CS and PSO on Rastrigin function

5.2. Runtime Performance

Analyzing the results in figure 7 and 8, it can be underattended that the runtimes of CS remain relatively low, while PSO runtime is increased within increases of dimensions. Consequently, optimization of the high dimensional problem has disturbed the performance of algorithm.

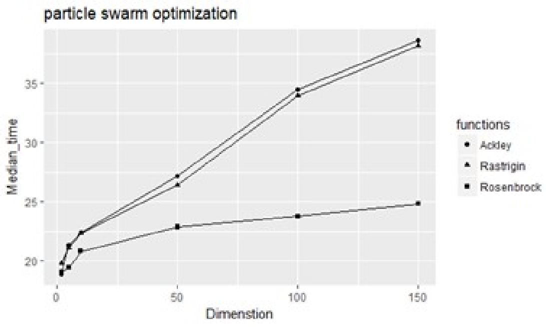

Figure7. PSO Runtime Performance

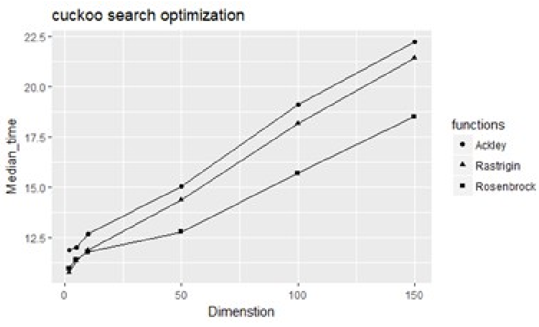

Figure 8. CS Runtime performance

6. CONCLUSION

In this paper, the authors have chosen tow algorithms based on swarm intelligence: 1-particle swarm optimization (PSO), 2-cuckoo search(CS) for comparison and analyzing on problems involving high dimensions. We have explained in details the functionality and pseudocode of the algorithms. Standard functions are using to evaluate the algorithms including Ackley, Rastrigin and Rosenbrock function. The algorithms have accomplished similar result for low dimensions problems. However, for higher dimensional problems up to 150, CS surpass PSO in terms of solution accuracy and runtime performances.

To be noted that the comparison has been performed for an almost basic version of algorithms. The authors have a confidence that this paper will become a beneficial reference for researchers to work on the accuracy and run-time performance comparison of basic and modified algorithms for the optimization problems that contain high dimensions.

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