Performance and Diversity of Gravitational Search Algorithm

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Abstract

GSA is a physic inspired optimization algorithm. It is based on how bodies in the universe are attracted to each other by gravitational force between them. The performance of GSA is studied here using benchmark functions. The diversity of the search agents of GSA is also studied. The findings show that research on improvement of GSA algorithm are needed, specifically in improving the search agents' diversity.

Keywords: *Gravitational search algorithm (GSA), optimization.*

1. Introduction

In recent years many nature inspired optimization algorithms had been proposed. Among these algorithms is GSA. GSA is proposed by Rashedi, Nezamabadi-pour, and Saryazdi in 2009 [1]. It is inspired by physical phenomena of how bodies in the universe are attracted towards each other by gravitational force. This phenomenon is explained by the Newton's gravitational law and Newton's second law of motion. The bigger a body's mass is the stronger its attraction force towards another bodies. The acceleration of the bodies moving the universe is inversely proportional with the mass and proportional to the force.

In GSA the bodies are analogous to the search agents while the search space is the universe of the GSA. Every search agents in GSA has masses assign to them where the values are dependent on the quality of the solution proposed by the agents. Similar to the physical phenomenon, agent with better quality solution has larger mass. Therefore eventually all agents of GSA are clustered around the fittest agent. GSA was claimed to perform generally better than particle swarm optimization (PSO), genetic algorithm and central force optimization [1] and better compared to existing algorithm in solving several problems [2], [3].

Here, the algorithms' performance in achieving or getting close to ideal solution and the diversity of their search agents throughout the search process are studied using the CEC2014's benchmark functions. Agents' diversity is an important aspect in optimization algorithms. It ensures search space is adequately explored and global optimum is found instead of local optimum [4]. For benchmarking purpose GSA is compared with PSO.

In the following section GSA is presented in detail. The experiment is presented and the results are discussed in section 3. Finally this paper is concluded in section 4.

2. Gravitational Search

GSA starts with random initialization of the agents, X_i, in the search space. The agents' positions represent the solutions suggested. The position of agent i^{th} is,

$$X_i = \left(x_i^1, x_i^2, \dots, x_i^d\right) \qquad i = 1,2,\dots,N \tag{1}$$

where x_i^d denoted the position of an agent at dimension d^{th}. The fitness of each agent's position is evaluated

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using problem dependent fitness function. Given that an agent's fitness at iteration t is represented as, $fit_i(t)$, the mass of the agents is calculated as follow;

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{2}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{3}$$

The $best(t)$ and $worst(t)$ represent the best and worst fitness among the agents in the population. These values are selected depending on whether the problem to be optimized is a maximization or minimization problem. Assuming a minimization problem, the definitions of these values are as follow;

$$best(t) = min\{fit_1(t), fit_2(t), \ldots, fit_N(t)\} \tag{4}$$

$$worst(t) = max\{fit_1(t), fit_2(t), \ldots, fit_N(t)\} \tag{5}$$

The masses are then used to calculate the force of an agent towards other agents, $F_{ij}^d(t)$.

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon}(x_j^d(t) - x_i^d(t)) \tag{6}$$

$R_{ij}(t)$ is the Euclidian distance between agent ith and jth. A small constant ε is added to avoid division by zero when the distance between the agents is zero. $M_{pi}(t)$ and $M_{aj}(t)$ are passive and active gravitational mass of agent ith and jth respectively. *G(t)* is the gravitational constant at time t. The equations for $M_{pi}(t)$, $M_{aj}(t)$ and *G(t)* are;

$$M_{pi}(t) = M_{ai}(t) = M_i(t) \tag{7}$$

$$G(t) = G_0 \times e^{-\beta \frac{t}{T}} \tag{8}$$

G_o is the gravitational constant at the start of the universe. This is typically set to 100. β is another constant and normally set to 20. *T* is the total number of iteration.

The total force acting on agent ith is;

$$F_i^d(t) = \sum_{j=1, j \neq i}^{N} rand_j F_{ij}^d(t) \tag{9}$$

where, $rand_j$ is a random number in the interval [0,1].

The agents in GSA are also subjected to Newton's law of motion, where the acceleration of a body is directly proportional and in the same direction as the net force acting on itself and inversely proportional to its mass. According to this law of motion, the acceleration of agent ith over dimension dth, $\alpha_i^d(t)$ can be calculated using the following equation;

$$\alpha_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{10}$$

The agents' velocities and positions are then updated using the equations below;

$$v_i^d(t) = rand_i^d \times v_i^d(t-1) + \alpha_i^d(t) \tag{11}$$

$$x_i^d(t) = x_i^d(t-1) + v_i^d(t) \tag{12}$$

The fitness of the whole population is evaluated first before best and worst values are identified. The agents in the population are then moved to new position.

3. Experiments

The algorithm is tested using the CEC2014's benchmark functions[1], consisting of unimodal, multimodal, hybrid and composite functions. For benchmarking purpose the performance of GSA is compared with PSO, which is considered as a landmark optimization algorithm [5]. Both algorithms use 100 search agents and the maximum iteration is 2000. PSO's c_1 and c_2 are set to 2 while GSA's G_o and β are set to 100 and 20 respectively. The diversity is calculated based on the positions of the agents with respect to each other [6].

The performance of GSA and PSO is presented in table 1. Based on Wilcoxon signed rank test with α=0.05, significant difference exist between GSA and PSO. Contradict to the findings in [1], it is found here that GSA does not outperform PSO. This could be contributed to lack of diversity (figure 1), where the agents in GSA clustered together much faster than PSO thus causing inefficient search by the agents.

Table 1. Main parameters

	Function	Ideal fitness	GSA	PSO
Unimodal	f1	100	67689680	23317468
	f2	200	96165370	1617145
	f3	300	137183.3	20228.39
Simple Multimodal	f4	400	865.8666	640.0601
	f5	500	519.9997	521.0929
	f6	600	647.4421	629.9419
	f7	700	702.1281	700.0133
	f8	800	1074.349	861.7606
	f9	900	1248.491	1050.632
	f10	1000	8259.619	2592.724
	f11	1100	9296.961	8036.232
	f12	1200	1200.003	1202.847
	f13	1300	1300.481	1300.624
	f14	1400	1400.288	1400.592
	f15	1500	1754.584	1520.159
	f16	1600	1622.531	1621.684
Hybrid Functions	f17	1700	2465942	2738877
	f18	1800	32085608	2697.624
	f19	1900	1943.759	1968.202
	f20	2000	59836.91	12246.31
	f21	2100	1911741	1850849
	f22	2200	4182.688	3121.514
Composite Functions	f23	2300	2500	2648.063
	f24	2400	2600.102	2676.316
	f25	2500	2700	2721.784
	f26	2600	2800.081	2771.405
	f27	2700	4568.71	3731.154
	f28	2800	6199.133	5374.668
	f29	2900	3100.156	11664505
	f30	3000	219235.9	39538.72

[1] Definition of CEC2014's benchmark functions: http://www.ieee-wcci2014.org/accepted-competitions.htm

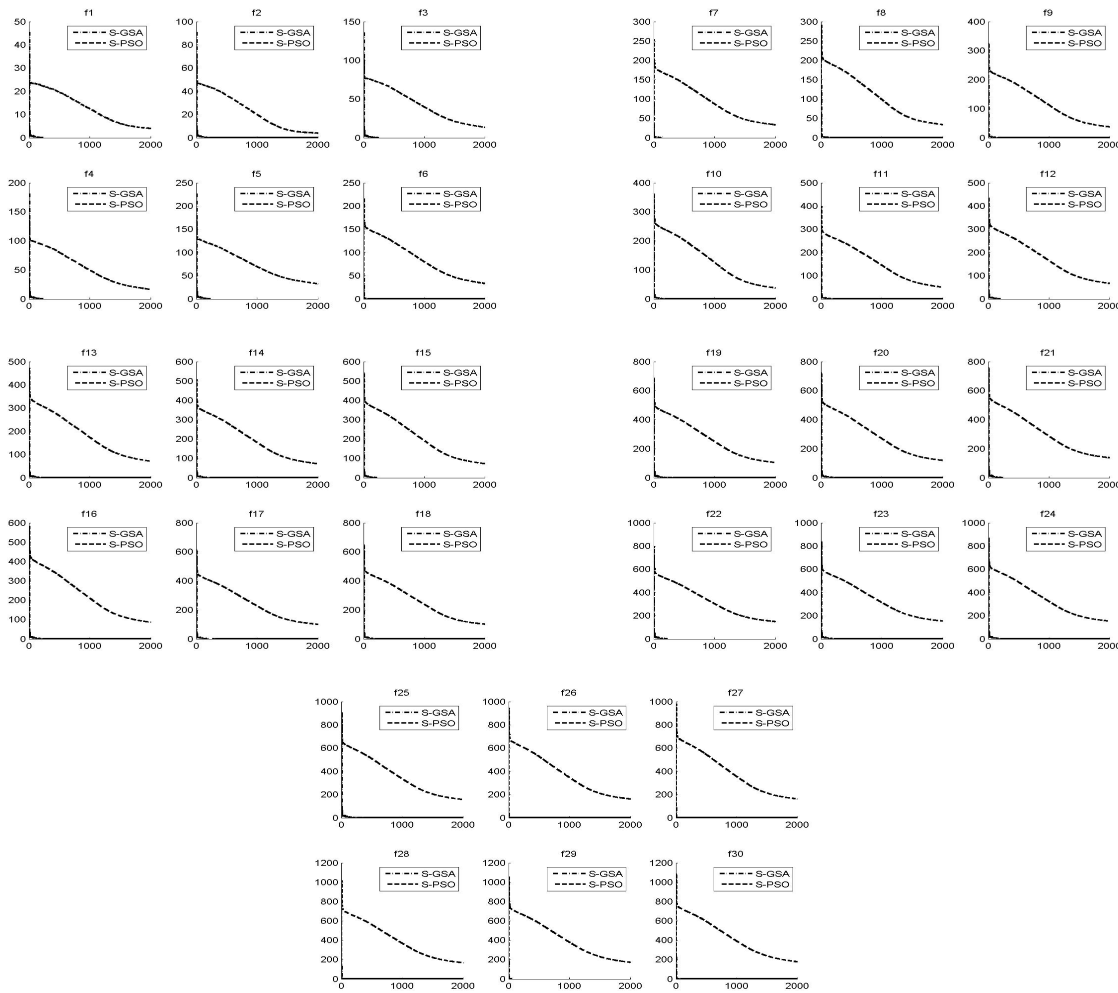

Figure 1. Diversity

4. Conclusion

GSA is an optimization algorithm which is inspired by physical phenomenon. The finding shows that as a young algorithm more works need to be done to improve GSA, especially in improving diversity of the agents so that search space is adequately explored and good performance can be achieved.

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