A Modified Gravitational Search Algorithm for Continuous Optimization

Emerson Hochsteiner de Vasconcelos Segundo
Mechanical Eng. Grad. Program, Pontifical Catholic University of Parana, Curitiba, PR, Brazil
e.hochsteiner@gmail.com

Gabriel Fiori Neto
Industrial and Systems Eng. Graduate Program (PPGEPS), Pontifical Catholic University of Parana (PUCPR), Curitiba, PR, Brazil
meudeu@gmail.com

Andre Mendes da Silva
Mechatronics Engineering Undergraduate Program, Pontifical Catholic University of Parana, Curitiba, PR, Brazil
andremendes1991@gmail.com

Viviana Cocco Mariani
Mechanical Engineering Graduate Program, Pontifical Catholic University of Parana, and Electrical Engineering, Federal University of Parana, Curitiba, PR, Brazil
viviana.mariani@pucpr.br

Leandro dos Santos Coelho
Industrial and Systems Eng. Graduate Program, Pontifical Catholic University of Parana, and Electrical Engineering, Federal University of Parana, Curitiba, PR, Brazil
leandro.coelho@pucpr.br

ABSTRACT
The gravitational search algorithm (GSA) is a stochastic population-based metaheuristic inspired by the interaction of masses via Newtonian gravity law. In this paper, we propose a modified GSA (MGSA) based on logarithm and Gaussian signals for enhancing the performance of standard GSA. To evaluate the performance of the proposed MGSA, well-known benchmark functions in the literature are optimized using the proposed MGSA, and provides comparisons with the standard GSA.

Categories and Subject Descriptors
G.1.6 [**Mathematics of Computing**]: Optimization—*Global Optimization*; I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic methods*

Keywords
Gravitational Search Algorithm; Optimization

1. INTRODUCTION
Gravitational search algorithm (GSA), proposed by Rashedi et al. [1], is a versatile population-based metaheuristic recently proposed inspired on the law of gravity and mass interaction for global optimization. There are several advanced GSA variants available in the literature to obtain better performance than the original GSA, such as approaches based chaos theory [2], oppositional operator [3], and quantum bits [4].

In this paper, we propose a modified GSA (MGSA) by introducing a new operator to update the velocities to diminish premature convergence and local minima for a minimization problem. In this context, the main purpose of this paper is to verify that the search ability of GSA can be enhanced by modification to update the velocities logarithm and Gaussian signals instead to uniform distribution signals. GSA and MGSA are used to optimize well-known benchmark functions and some simulation results are compared. Obtained results confirm the efficiency of the proposed MGSA.

The remainder of this paper is organized as follows: In Section 2 we provide a brief summary of GSA and explains the MGSA. Section 3 introduces the well-known benchmark functions and optimization results. Finally, we provide conclusions in Section 4.

2. GRAVITATIONAL SEARCH ALGORITHM
In GSA, agents are considered as objects and their performance are measured by their masses, with all objects attracting each other by the gravity force, while this force causes a global movement of all objects towards the objects with heavier masses [3]. This approach provides an iterative method that simulates mass interactions, and moves through a multi-dimensional search space under the influence of gravitation.

To describe the GSA, consider a system with N agents (masses) in which the position of the ith agent is represented by:

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

where n is the search space dimension and x_i^d defines the position of the ith agent in the dth dimension. At any time (or current iteration) t the force acting between the ith mass and the jth mass based on Newtonian gravitation theory is defined as [3]:

$$\mathbf{f}_{ij}(t) = G(t)\frac{M_i(t)\cdot M_j(t)}{R_{ij}(t)+\varepsilon}\left(\mathbf{x}_j(t)-\mathbf{x}_i(t)\right) \tag{2}$$

where $G(t)$ is parameter which is reduced during iterations according to

$$G(t) = G_O e^{-\alpha\cdot\frac{t}{\max\_t}} \tag{3}$$

where max_t is the maximum of iterations, α is a constant value, M is the mass, R_{ij} is the distance and ε is a small value. It is then assumed that the total force acting on a mass is a randomly weighted sum of the individual forces (2), thus:

GECCO'14, July 12–16, 2014, Vancouver, BC, Canada.
ACM 978-1-4503-2662-9/14/07.

$$\mathbf{f}_i(t) = \sum_{j=1, j\neq i}^{N} r_j \cdot \mathbf{f}_{ij}(t) \quad (4)$$

where r_j is a uniformly distributed random number in the interval [0,1]. This allows the update of velocities and positions according to [3]:

$$\begin{aligned} \mathbf{v}_i(t+1) &= r_i \cdot \mathbf{v}_i(t) + \mathbf{a}_i(t) \\ \mathbf{x}_i(t+1) &= \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \end{aligned} \quad (5)$$

where

$$\mathbf{a}_i(t) = \frac{\mathbf{f}_i(t)}{M_i(t)} \quad (6)$$

After this step masses are updated according to:

$$\begin{aligned} m_i(t) &= \frac{f_i(t) - w(t)}{b(t) - w(t)} \\ M_i(t) &= \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \end{aligned} \quad (7)$$

where b and w indicate the best and worst objective function values and f is the objective function. The procedure is then repeated until some convergence criterion is satisfied. Summarizing, the classical GSA is composed of following steps:

(i) Randomized initialization of the agents including positions and velocities using uniform distribution;

(ii) Fitness evaluation for each agents;

(iii) Update $G(t)$, $b(t)$, $w(t)$ and $M_i(t)$;

(iv) Calculation of the total force in different directions;

(v) Calculation of acceleration and velocity;

(vi) Updating agents' position;

(vii) Repeat steps (ii) to (vi) until a given stopping criterion related to the number of objective function evaluations is reached.

(viii) Return the best fitness computed at final iteration as a global fitness and the positions of the corresponding agent at specified dimensions as the global solution of that problem.

To improve the performance of GSA, a logarithm and Gaussian updating of the r_i is incorporated into MGSA by means of utilizing a modified version of the equation (5) given by following procedure:

if $ru > 0.5$ then $r_i \cdot = \ln(1/rd)/8$ else $r_i \cdot = 0.3 + 0.1 \cdot rg$

where ru and rd are uniformly distributed random numbers in the interval [0,1], and rg is a normally distributed pseudorandom number with mean 0 and standard deviation 1.

3. COMPUTATIONAL RESULTS

In order to test the performance of the proposed MGSA, two well-known benchmark functions are evaluated in N = 30 dimensions (50 runs). For all runs, we used the following parameters in GSA and MGSA: population size is set to 100 agents, stopping criterion (max_t) is equal to 3,000 iterations, G_0, is set to 100, and α = 20. Figure 1 shows mean best objective function (for the best solution) for the GSA and MGSA with 30 independent runs for the benchmark functions. It is evident from the Figure 1 that the MGSA is able to give better convergence trends for the Rosenbrock and Rastrigin functions.

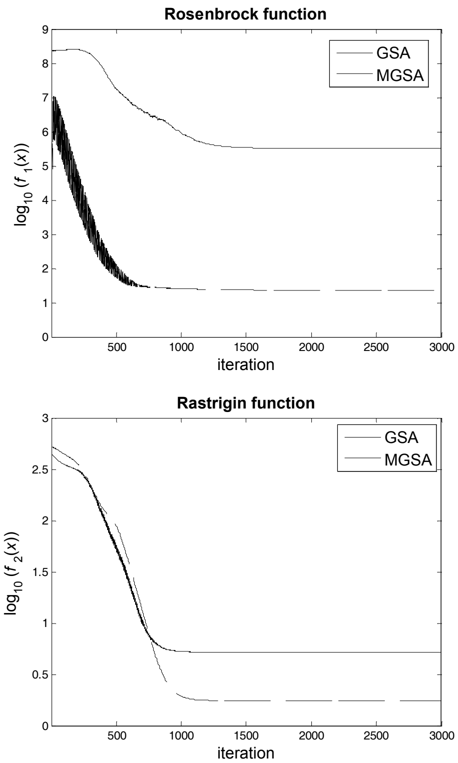

Figure 1. Comparison of mean best objective function (30 runs) for the GSA and MGSA.

4. CONCLUSION

In this paper, the proposed MGSA has been successfully implemented to solve two benchmark functions. It has a flexible and well-balanced mechanism for enhancing exploration and exploitation abilities. Simulation results show that MGSA achieves promising results and outperforms the classical GSA. In the future we may examine the performance of MGSA for other continuous optimization problems.

5. REFERENCES

[1] E. Rashedi, H. Nezamabadi-pour, and S. Saryazdi, 2009, GSA: A gravitational search algorithm, *Information Sciences*, 179(13):2232-2248.

[2] S. Gao, C. Vairappan, Y. Wang, Q. Cao and Z. Tang, 2014, Gravitational search algorithm combined with chaos for unconstrained numerical optimization, *Applied Mathematics and Computation,* 231:48-62.

[3] L. S. Coelho, V. C. Mariani, N. Tutkun and P. Alotto, 2014, Magnetizer design based on a quasi-oppositional gravitational search algorithm, *IEEE Transactions on Magnetics*, 50(2):705-708.

[4] B. Ji, X. Yuan, Z. Chen and H. Tian, 2014, Improved gravitational search algorithm for unit commitment considering uncertainty of wind power, *Energy*, 67:52-62.