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An effective gbest-guided gravitational search algorithm for real-parameter optimization and its application in training of feedforward neural networks

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ABSTRACT

Gravitational search algorithm (GSA) is a recently introduced meta-heuristic that has shown great performance in numerical function optimization and solving real world problems. GSA provides an excellent social interaction between its search agents. This social interaction results in admirable exploration of the search space and gives a unique social component to GSA. However, the social interaction is not able to exploit good solutions in an efficient manner. To overcome this problem, a novel algorithm named as gbest-guided gravitational search algorithm (GG-GSA) has been proposed by utilizing the global best (gbest) solution in the force calculation equation of GSA. The employment of gbest solution in any optimization algorithm is a tough task and can lead to premature convergence. In the proposed algorithm, the gbest solution is used adaptively and is able to achieve a better trade-off between exploration and exploitation. The performance of the proposed algorithm is compared with GSA and its variants on different suites of well-known benchmark test functions. The experimental results show that the GG-GSA performs better than other algorithms for most of the benchmark test functions. Furthermore, to test the ability of the proposed algorithm in solving real world applications, training of feedforward neural network problem is chosen. The results demonstrated the exceptional performance of GG-GSA on real world data-set.

1. Introduction

In the last three decades nature inspired algorithms have been widely investigated and applied to various real-world optimization problems, e.g., image processing [1,2], data clustering [3], neural network training [4,5], graph theory [6], economic dispatch [7], etc. Among the class of nature inspired algorithms, the gravitational search algorithm (GSA) is a novel meta-heuristic search algorithm proposed by Rashedi et al. [8]. This physics based algorithm is inspired by the Newtons's law of gravity and motion. In GSA, the search entities are group of masses (search agents) which communicate with each other on the basis of Newtonian gravity and laws of the motion. In GSA, there are three main calculations, i.e., gravitational force calculation between different agents, acceleration calculation and velocity calculation of each agent. In gravitational force calculation, an agent tries to search for global optimum by learning from K_{best} selected agents. K_{best} is a linearly decreasing function of time and initialized to population size. Initially, the learning from K_{best} agents results in the good exploration of the search space but with the lapse of time only fewer agents are selected for learning which results in exploitation of good solutions. In this way GSA is able to provide a good trade-off between exploration and exploitation.

However, some researchers try to enhance the performance of GSA by finding different ways for balancing exploration and exploitation. One common trend is to hybridize GSA with other existing metaheuristics. Mirjalili and Hashim [9] introduced a hybrid approach by combining particle swarm optimization and gravitational search algorithm (PSOGSA). In PSOGSA, the social thinking of PSO is embedded into GSA. Li et al. [10] proposed a combination of differential evolutionary algorithm and gravitational search algorithm for unconstrained optimization problems. For image segmentation, a novel hybrid genetic algorithm based gravitational search algorithm was proposed by Sun and Zhang [11]. Jayaprakasam et al. [12] proposed PSOGSA-E by adding the cognitive component of PSO to PSOGSA algorithm and claimed that their proposed algorithm can better deal with premature convergence problem. A hybrid approach based on cuckoo search-gravitational search al-

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gorithm (CS-GSA) is presented by Naik et al. [13] to enhance the exploration capability of GSA. In adaptive gbest-guided gravitational search algorithm (GGSA), gbest-guidance inspired by PSO is used to increase the velocity of the agents towards the memorized best solution for gaining better convergence speed [14]. In GGSA, the global best solution (gbest) is utilized adaptively to provide a balance between exploration and exploitation. Modified gravitational search algorithm (MGSA) [15], employs the idea of local best solution (pbest) and gbest solution taken from PSO into GSA velocity calculation to enhance the exploration and exploitation of GSA. Darzi et al. [16] raised the issue of losing optimal trajectory in GSA as standard GSA does not store any solution into its memory. They introduced a new version of gravitational search algorithm (MBGSA) based on memory which is inspired by PSO pbest solutions. Recently, Sun et al. [17] modified the gravitational force equation by adapting k local neighbors topology and also add the guidance of global best agent (gbest) to propose locally informed gravitational search algorithm (LIGSA). In LIGSA, every search agent is getting guidance from its neighbor and gbest solution. Initially, the priority is given to learning from neighbors for exploration but, after certain number of iterations the search process is mainly guided by gbest solution for enhanced exploitation. It has been shown, that LIGSA is able to find a better trade-off between exploration and exploitation than standard GSA and its variants.

Another common incline towards improvement of GSA performance is to add some operators into the standard GSA. Disruption based operator was employed by Sarafrazi et al. [18] to further adaptively explore and exploit the search space. Opposition-based learning operator introduced by Shaw et al. [19] provides better population initialization and also helps in improving the efficiency of GSA to deal with local minima. Doraghinejad et al. [20] utilized black hole theory to improve the exploration and exploitation capabilities of GSA. However, there is an important concern that above-mentioned variants of GSA seem to be difficult to simultaneously achieve the balance between exploration and exploitation of the GSA. Therefore, a good number of research attempts are required to establish new efficient gravitational search algorithms for optimization problems.

Motivated by the observations mentioned above, in this paper a novel GSA variant, gbest-guided gravitational search algorithm (GG-GSA) is proposed. In GG-GSA, a gbest-guidance is introduced to emphasize the movement of search agents towards the group-best solution (gbest solution) among the current population of agents, adaptively. For different real world problems, the proposed algorithm can provide a better trade-off between exploration and exploitation as compares to GSA and its variants. To prove GG-GSA has better capabilities to search for optimal solution, it is applied to well-known test functions. The proposed algorithm has also been applied in training of feedforward neural networks for classification problems and its performance has been compared with seven other state of the art algorithms. The results clearly show that the proposed algorithm is able to find better objective function values in most of the considered classification problems. The goal of this paper is twofold.

- Firstly, a novel gbest-guided GSA is proposed and compared with standard GSA and its recent variants on standard benchmark function problems.
- Secondly, a comparative study of the performance of GG-GSA with respect to other state of the art metaheuristics on the problem of training of feedforward neural networks (FNN).

The rest of the paper is organized as follows: Section 2 presents the rudimentary concepts of FNN. Section 3 gives a brief review of GSA while in Section 4 the proposed algorithm, GG-GSA is presented. In Section 5, the performance of the proposed algorithm is shown through experimental results. Section 6 depicts the application of GG-GSA for training of feedforward neural networks. Finally, Section 7 concludes the work with directions towards the future extension of the work.

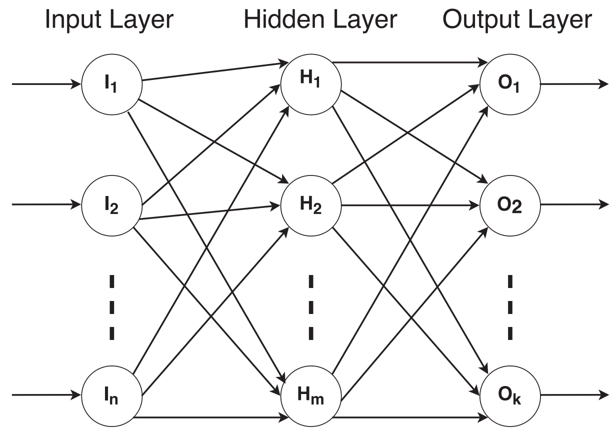

Fig. 1. A representative FNN architecture.

2. Feedforward neural networks

Feedforward neural networks (FNN) secure a special standing among the neural network architectures because of its unique no cycle (without loop) formation. FNN is composed of several processing units known as neurons spread over different layers where each layer is fully linked with successive one [21]. The first layer of the FNN is the input layer which introduces the input variables to neural network and its last layer is known as output layer. All the layers lie between the input layer and output layer are hidden layers.

In FNN, the processing units (neurons) are connected in one-directional fashion. Connections are portrayed by weights which are real number lies between interval [−1,1]. A very simple architecture of single hidden layer FNN is shown in Fig. 1. In this representative architecture, there are n number of nodes in the input layer, m number of nodes in the hidden layer and k number of nodes exists in the output layer. The output of each node in the hidden layer and output layer is calculated in two steps. First, the weighted summation of inputs to the node is calculated and second, an activation function is utilized to trigger the output of neurons based on the value of summation. There are various activation functions available in literature. The sigmoid function is one of the most applied and popular among other activation functions. The procedure of calculating output of the FNN is as follows:

The inputs to a hidden layer node is weighted and their sum can be calculated by Eq. (1),

$$s_j = \sum_{i=1}^{n} (W_{ij}.X_i) - b_j, \quad j = 1, 2, 3 \ldots, m \tag{1}$$

where n denotes the number of input nodes, W_{ij} represents the connection weight from ith node of the input layer to the jth of the hidden layer. b_j denotes the bias (threshold) of the jth hidden node and X_i is the value of ith input. The calculation of output of each hidden layer node is done by sigmoid function as follows:

$$S_j = sigmoid(s_j) = \frac{1}{(1 + exp(-s_j))}, \quad j = 1, 2, 3 \ldots, m \tag{2}$$

The inputs to the output layer nodes are also weighted and their sum is calculated as:

$$o_h = \sum_{j=1}^{m} (W_{jh}.S_j) - b'_j, \quad h = 1, 2, 3 \ldots, k \tag{3}$$