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A gravitational search algorithm for multimodal optimization

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ABSTRACT

Gravitational search algorithm (GSA) has been recently presented as a new heuristic search algorithm with good results in real-valued and binary encoded optimization problems which is categorized in swarm intelligence optimization techniques. The aim of this article is to show that GSA is able to find multiple solutions in multimodal problems. Therefore, in this study, a new technique, namely Niche GSA (NGSA) is introduced for multimodal optimization. NGSA extends the idea of partitioning the main population (swarm) of masses into smaller sub-swarms and also preserving them by introducing three strategies: a *K*-nearest neighbors (*K-NN*) strategy, an elitism strategy and modification of active gravitational mass formulation. To evaluate the performance of the proposed algorithm several experiments are performed. The results are compared with those of state-of-the-art niching algorithms. The experimental results confirm the efficiency and effectiveness of the NGSA in finding multiple optima on the set of unconstrained and constrained standard benchmark functions.

1. Introduction

Many practical scientific and engineering problems comprise objective functions with multimodal behavior that require optimization methods to find more than one solution. A multimodal problem generally has a number of global optima and several local optima that might be good alternatives to the global ones. On the other hand, the local optima could be excellent alternative solutions in many cases. Therefore, it is desirable in many applications to find the location of all global optima and also other local optima during a search process [1,2]. At least there are two practical reasons for finding multiple optima of an optimization problem [3]. First, by finding multiple optima, the chance of locating the global optimum may be improved. Second, in a design context, identifying a diverse set of high-quality solutions (multiple optima) will give the designer some notion about the nature of the problem, perhaps, may suggest innovative alternative solutions [3].

Traditional heuristic search algorithms like genetic algorithms (GAs) converge towards a single solution (this is the so-called genetic drift phenomenon). GAs perform well in locating a single optimum but fail to provide multiple solutions [2,4], therefore they are not suitable for multimodal optimization. GAs often lose multiple solutions (widely different solutions) due to three effects [5,6]: selection pressure, selection noise, and operator disruption. Unfortunately, other types of heuristic algorithms including standard evolutionary algorithms (e.g. evolutionary programming (EP), evolutionary strategy (ES), differential evolutionary (DE), GA) and standard swarm intelligence (SI) techniques (e.g. ant colony optimization (ACO), particle swarm optimization (PSO)) suffer from the similar disadvantage.

To overcome this problem, many theoretical and empirical studies have been realized to find multiple solutions to multimodal optimization problems using different types of heuristic algorithms especially GAs. Optimization methods that are able to find the location of multiple optima in multimodal problems are known as niching methods [7]. Niching methods partition the population in such a way that each group of the main population focuses on a different possible solution in a single run of a heuristic search. In other words, these methods try to prevent the search from premature convergence and hence aim at preserving diversity in the population and promote the maintenance of stable sub-populations. In the optimization terminology, a niche is referred to as a peak of the fitness landscape, while a species is defined as a subpopulation of similar individuals populating a niche (each subpopulation in the partitioned population).

SI studies the collective behavior of systems composed of many individuals interacting locally with each other and with their environment. Swarms inherently use forms of decentralized control and self-organization to achieve their goals. In SI systems the agents follow very simple rules, although there is no centralized control structure dictating how individual agents should behave. Here, social interactions provide the basis for unguided problem solving. Gravitational Search Algorithm (GSA) is one of the SI-based optimization algorithms which introduced by Rashedi et al. in 2009 based on the metaphor of gravitational interaction

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between masses [8]. GSAs are computational models that emulate the law of gravity to solve optimization problems. A GSA comprises a set of mass elements (swarm) and a set of physical inspired operators. According to the Newtonian gravity and motion theories, the population evolves towards increasingly better regions of the search space by simulation of gravity and motion laws. The previous works have revealed the efficiency of the GSA as a global optimizer in solving various nonlinear continuous benchmark functions [8] and its binary version (BGSA) [9] in solving binary encoded problems. Moreover, the results obtained in [10–12] confirm that GSA is a suitable tool for classifier design, parameter identification of hydraulic turbine governing system, and synthesis of thinned scanned concentric ring array antenna, respectively.

Theoretically, GSA belongs to the class of SI-based heuristic algorithms. Rashedi et al. [8] practically gave a comparative study between GSA and a small number of well-known swarm algorithms like PSO. The obtained results reveal that GSA has a merit in the field of optimization. Also, to theoretically highlight the differences between GSA and other heuristic algorithms some distinct features of it has been noted by Rashedi et al. [8].

As mentioned above, GSA artificially simulates the Newton theory that says: every particle in the universe attracts every other particle and the gravity is a force that pulls together all matters. Based on this description, masses in GSA tend to converge towards each other, which in turn means convergence to the global optimum of the problem at hand. Similar to genetic drift in GAs, we refer to this phenomenon as gravity drift. Therefore, a simple GSA is unable to provide multiple solutions in multimodal problems in a single run of the search. Since introducing the standard GSA, there has not been any effort for providing a GSA version for handling multimodal problems. This paper deals with this issue and for this purpose some simple modifications are applied on the standard GSA to support niching in multimodal optimization. In other words, our aim is to show that the standard GSA with a small change is able to effectively handle multimodal problems. For simplicity, here we call the proposed algorithm as Niche GSA (NGSA).

This paper is organized as follows. Section 2 gives us a review on the related works. Section 3 provides a brief introduction to GSA. The proposed Niche GSA for multimodal problems is given in Section 4. The experimental study is illustrated in Section 5, where the performance of the algorithm will be evaluated on a set of benchmark functions. Finally, the paper is concluded in Section 6.

2. Background

Achieving a good method for multimodal optimization by heuristic algorithms will be possible if and only if population diversity is preserved. For the first time, Cavicchio [13] proposed his scheme in 1970, namely as preselection, to preserve the diversity of genetic algorithm. In preselection, each offspring competes with his parents for survival. The better one wins the competition and is transferred to the next population. Substituting the parents by their offspring is the main reason why in this scheme the diversity is preserved. De Jong in his thesis developed the preselection to achieve crowding scheme [14] in which for each offspring, CF (crowding factor) parents are selected at random and the most similar one to the offspring is chosen to be replaced. In crowding, similarity is calculated according to a genotypic measure. It is noted that in ordinary crowding, at each generation only a portion of current population G (generation gap), is selected based on a fitness proportionate strategy to reproduce the next generation.

Both preselection and crowding schemes are unable to find more than two peaks on multimodal problems due to replacement error [15,16]. Mahfoud proposed the deterministic crowding scheme to improve the standard one by reducing the replacement error by the following modifications [17]: (i) individuals are selected for reproduction by random selection strategy, (ii) genotypic similarity measures are replaced by phenotypic one, (iii) each offspring is compared only to its parents and replace the nearest parent if it has a higher fitness value (where in this way offspring and parents of identical niches compete for survival). Unfortunately, deterministic crowding suffers greatly from genetic drift just like its standard version [2].

The authors in [18] described an algorithmic and analytical framework which is applicable to a wide range of crowding algorithms. As an example they analyzed the probabilistic crowding niching algorithm. It is shown that in probabilistic crowding, subpopulations are maintained reliably, and they showed that it is possible to analyze and predict how this maintenance takes place.

Fitness sharing which is the most frequently used scheme for multimodal optimization was first proposed by Goldberg and Richardson [19]. Fitness sharing aims at effective formulation and preservation of stable niches. This scheme has been inspired by nature based on the idea that individuals in a particular niche should share the existing resources. Fitness sharing leads the search in unexplored regions of the search space by artificially decreasing fitness of solutions in crowded areas. According to this idea, the fitness value of a certain solution is degraded proportional to the existing solutions that are located in its neighborhood. Here, the neighborhood is defined in terms of a distance measure and specified by the parameter σ_{share} known as niche radius which is a user defined parameter. To do this, a penalty method is applied to penalize the solutions positioned in populated regions. In other words, for each solution, all other solutions are found in its niche radius and their fitness values are shared using the sharing function. Performance of fitness sharing scheme is highly dependent on value of niche radius which is the same for all peaks. This is the main disadvantage of fitness sharing because each peak needs its own niche radius while similar niche radius for all peaks may result in over- or under-discovering of them.

Mating two individuals from different niches may cause to produce the lethal individuals. The mating restriction scheme was proposed by Deb and Goldberg [20] to promote the effect of fitness sharing scheme. Based on this scheme, two individuals are allowed to mate only if they are within a certain distance of each other (given by the parameter σ_{mating} so-called as mating radius). Mating restriction may avoid the production of lethal individuals and therefore improve the algorithm performance. Sequential niching has been proposed by Beasley et al. in which the niches are discovered sequentially over time [1]. After identifying a niche, the search space is adapted such that to keep away other solutions from the region around the recent discovered solutions. This process is frequently applied in order to focus on unexplored regions and detect undiscovered niches.

In [21], several strategies of sharing have been reviewed and a new recombination schemes has been proposed to improve the efficiency of search algorithm. Finally, the study compares several sharing methods with other niching techniques such as clearing [22]. Among all niching GAs reviewed in this paper, clearing can be considered as the best method [21]. A species conservation genetic algorithm (SCGA) was presented in [3] to evolve parallel subpopulations for multimodal function optimization in which distributed elitism is used where, the population is divided into several species according to their similarity. Each of these species is built around a dominating individual called the species seed. The species seeds found in each generation are conserved by moving them into the next generation. The only difference between the simple GA (SGA) and SCGA is introducing two processes of the selection of seeds and the conservation of species into the main loop of SGA [3]. The proposed method in [23] combines the ideas of SCGA of