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Genetic Algorithm with adaptive elitist-population strategies for multimodal function optimization

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ABSTRACT

This paper introduces a new technique called adaptive elitist-population search method. This technique allows unimodal function optimization methods to be extended to efficiently explore multiple optima of multimodal problems. It is based on the concept of adaptively adjusting the population size according to the individuals' dissimilarity and a novel direction dependent elitist genetic operators. Incorporation of the new multimodal technique in any known evolutionary algorithm leads to a multimodal version of the algorithm. As a case study, we have integrated the new technique into Genetic Algorithms (GAs), yielding an Adaptive Elitist-population based Genetic Algorithm (AEGA). AEGA has been shown to be very efficient and effective in finding multiple solutions of complicated benchmark and real-world multimodal optimization problems. We demonstrate this by applying it to a set of test problems, including rough and stepwise multimodal functions. Empirical results are also compared with other multimodal evolutionary algorithms from the literature, showing that AEGA generally outperforms existing approaches.

1. Introduction

Genetic algorithms (GAs) have proven useful in solving a variety of search and optimization problems [2,8–10,22,24,39]. Many real-world problems require an optimization algorithm that is able to explore multiple optima in their search space. In this respect, GAs have demonstrated the best potential for finding the optimal solutions because they are population-based search approaches and have strong global optimization capabilities. However, in the standard GA for maximization problems, all individuals, which may be located on different peaks at the beginning of the search process, eventually converge to a single peak. Thus, it usually ends up with only one solution. If this solution is a local optimum, we call it premature convergence in GAs. This phenomenon is even more serious in GAs with elitist strategy, which is a widely adopted method to improve GAs' convergence [16].

Over the years, various population diversity enhancement mechanisms have been proposed, which enable GAs to maintain a diverse population of individuals throughout their search, to avoid convergence of the population to a single peak and to allow GAs to identify multiple optima in a multimodal function landscape. However, various current population diversity enhancement mechanisms have not demonstrated themselves to be very efficient as expected. The efficiency problems, in essence, are related to some fundamental dilemmas in GAs implementation. We believe any attempt to improve the efficiency of GAs has to compromise between these two dilemmas:

- *The elitist search versus diversity maintenance dilemma*:
  GAs are expected to be global optimizers with global search capability to encourage exploration of the global optimal solutions. So the elitist strategy is widely adopted in the GAs' search processes to improve the chance of finding the global optimal solution. Unfortunately, the elitist strategy concentrates on some "super" individuals, but reduces the diversity of the population, and in turn leads to premature convergence. Contrarily, GAs need to maintain the diversity of the population in their search processes to find the multiple optimal solutions. How to balance both the elitist search and the diversity maintenance is important for constructing an efficient multimodal GA. Some researchers have attempted to handle the dilemma, e.g., Mahfoud's Deterministic Crowding methods [34], Petrowski's Clearing Procedure [41] and Li's Species Conserving Genetic Algorithm (SCGA) [32].
- *The algorithm effectiveness versus population redundancy dilemma*:
  For many GAs, we can use a large population size to improve the chance to obtain the global and multiple optima for optimization problems. However, the large population size will notably increase the computational complexity of the algorithms and

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generate a lot of redundant individuals in the population, thereby decrease the efficiency of GAs.

Our idea in this study is to strike a tactical balance between the two contradictory dilemmas. We propose a new adaptive elitist-population search technique to identify and search for multiple optima efficiently in the multimodal function landscape. The technique is based on an elitist population with a dynamically adapting size and the adoption of a series of new GA mechanisms: a specific definition of an elitist individual for the multimodal function landscape, a new principle for the individual's dissimilarity, and a new set of direction dependent elitist genetic operators. Combining this technique with GA, we propose a novel multimodal GA—adaptive elitist-population based genetic algorithm (AEGA). AEGA was first proposed by the authors [31]. This paper describes an improved version of AEGA. Using multiple test functions, we demonstrate empirically that our proposed approach generally outperforms the existing multimodal evolutionary algorithms reported in the literature.

To illustrate our technique, we will use unconstrained optimization problems of real-valued functions, defined over an array of real numbers. Where no confusion could occur we denote the objective function by $f(x)$. AEGA in this paper makes no distinction between genotypes and phenotypes. Thus, genetic operators will be applied directly to individuals represented by arrays of real numbers. Note that none of the above restrictions are required for our technique to be applicable. The only reason for imposing them is for simplicity of presentation.

The remainder of this paper is organized as follows. The next section describes related work relevant to our proposed technique. Section 3 introduces the adaptive elitist-population search technique and describes the implementation of the algorithm. Section 4 presents the results from a series of experiments on a set of test functions, and the comparison of our results with other multimodal evolutionary algorithms. Sections 5 and 6 present the analyses of the parameter choice in AEGA. Section 7 presents the conclusion and some future directions of research.

2. Related work

When applying GAs to multimodal optimization problems, it is very important to maintain two apparently contradictory requirements, which are to preserve promising individuals from one generation to the next and maintain the diversity of the population [32]. This section briefly reviews the existing methods developed to address the related issues: elitism, niche formation methods and other parallel subpopulations search methods.

2.1. Elitism

Many elitist methods in the literature on GAs preserve the best solution in different ways. For instance, Whitley [49] proposed a GENITOR approach that generates just one child for each cycle, which then replaces the worst individual of the population. Eshelman [18] introduced the CHC Adaptive Search algorithm to select the best M (the population size) individuals from the population, which merges all parents and offspring together. For multimodal optimization, Mahfoud's Deterministic Crowding methods [34] only replace a parent if the competing offspring is better. Petrowski's Clearing Procedure [41] preserves the fitness of the dominant individual, while it resets the fitness of all the other individuals of the same subpopulation to zero. Li's SCGA [32] copies the dominating individual of each of the species into the next generation as the species' seeds.

The elitism strategies have been also widely used in implementations of other evolutionary algorithms (EAs). For instance, Costa and Oliveira [12] proposed evolution strategy (ES) with elitist method for multiobjective optimization. Cortés et al. [11] proposed a novel viral systems (VS) with elitist strategy to deal with combinatorial problems. Zhang et al. [51] proposed an efficient population-based incremental learning (PBIL) algorithm with elitist strategy. PBIL is one of the simplest estimation of distribution algorithms (EDAs). However, it is pointed out that "elitist strategies tend to make the search more exploitative rather than explorative and may not work for problems in which one is required to find multiple optimal solutions" [43].

2.2. Evolving parallel subpopulations by niching

Niching methods extend GAs to problems that require to locate and maintain multiple optima through parallel subpopulations' search.

Cavicchio [6] proposed a preselection scheme in which a child replaces the worse parent if the child's fitness is higher than that of the worse parent. De Jong [15] generalized the preselection technique and suggested a crowding scheme. The approach works by reproducing and killing off a fixed percentage of the population each generation. Each newly generated member must replace an existing one, preferably the most similar one. Subsequently, two further variants of crowding, Deterministic Crowding [34] and Probabilistic Crowding [35], were proposed. Both of them use the tournament selection and hold tournaments between similar children and parents. The main difference between them is that the former uses a deterministic acceptance rule, while the latter uses probabilistic tournaments. Cadeño and Vemuri [7] proposed the Multi-Niche Crowding GA (MNC GA) for dynamic landscapes. The algorithm introduces the concept of crowding selection to promote mating among members with similar traits while allowing many members of the population to participate in mating. Then the MNC GA uses the worst among most similar replacement (WAMS) policy to promote competition among members with similar traits while allowing competition among members of different niches.

In another way, fitness sharing is frequently employed to induce niching behavior in GAs. Goldberg and Richardson [23] proposed a sharing scheme in which the idea is to force the individuals of the populations to share available resources by dividing the populations into different subpopulations on the basis of the similarity of the chromosomes. To implement the sharing scheme, a simple linear function called sharing function $Sh(d_{i,j})$ is adopted as a function of $d_{i,j}$, which is the distance between two individuals x_i and x_j. The sharing function is evaluated for each pair of N individuals in the population, and then the sum $Sh_i = \sum_{j=1}^{N} Sh(d_{i,j})$ is computed for each individual x_i. Finally, the fitness of this individual is adjusted by dividing by Sh_i. This sharing scheme was shown [23] to be better able to preserve diversity than the crowding scheme and was successfully applied to solve a variety of multimodal functions. To make the notion of species clearer, Yin and Germay [50] introduced a Clustering methodology to the sharing scheme in which each population is divided into clusters directly, but it does not increase any more diversity than the classical sharing scheme does.

The main drawbacks to use sharing are: (i) setting dissimilarity threshold σ_{share} requires a priori knowledge of how far apart the optima are [13,34]; and (ii) the computational complexity of niche counts is $O(N^2)$ per generation [37,50]. To reduce the computational complexity of sharing scheme, Beasley at al. [3] proposed the Sequential Fitness Sharing. It works by iterating a traditional GA, and maintaining the best solutions of each run off-line. To avoid converging to the same area of the search space multiple times, whenever sequential fitness sharing locates a solution, it depresses the fitness landscape at all points within some dissimilarity threshold σ_{share} of that solution.