Finding Multiple Solutions with GA in Multimodal Problems

Marcos Gestal
University of A Coruña, Spain

Mari Paz Gómez-Carracedo
University of A Coruña, Spain

INTRODUCTION

Traditionally, the Evolutionary Computation (EC) techniques, and more specifically the Genetic Algorithms (GAs) (Goldberg & Wang, 1989), have proved to be efficient when solving various problems; however, as a possible lack, the GAs tend to provide a unique solution for the problem on which they are applied. Some non global solutions discarded during the search of the best one could be acceptable under certain circumstances. The majority of the problems at the real world involve a search space with one or more global solutions and multiple local solutions; this means that they are multimodal problems (Harik, 1995) and therefore, if it is desired to obtain multiple solutions by using GAs, it would be necessary to modify their classic functioning outline for adapting them correctly to the multimodality of such problems.

MOTIVATION

This chapter tries to establish the basis for the understanding of multimodality where, firstly, the characterisation of the multimodal problems will be attempted. It would be also tried to offer a global view of some of the several approaches proposed for adapting the classic functioning of the GAs to the search of multiple solutions. Lastly, the contributions of the authors will be also showed.

BACKGROUND: CHARACTERIZATION OF MULTIMODAL PROBLEMS

The multimodal problems can be briefly defined as those problems that have multiple global optimums or multiple local optimums.

For this type of problems, it is interesting to obtain the greatest number of solutions due to several reasons; on one hand, when there is not a total knowledge of the

Figure 1. Rastrigin function
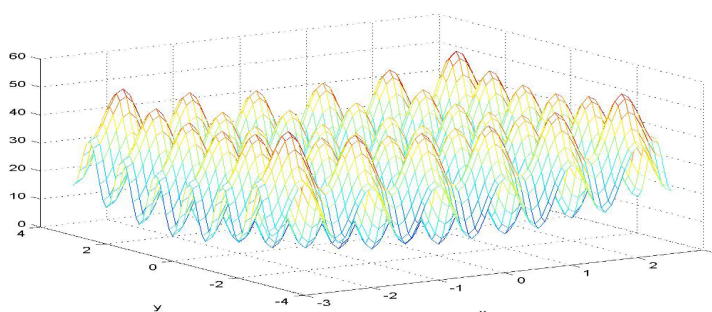
problem, the solution obtained might not be the best one as it can not be stated that no better solution could be found at the search space that has not been explored yet. On the other hand, although being certain that the best solution has been achieved, there might be other equally fitted or slightly worst solutions that might be preferred due to different factors (easier application, simpler interpretation, etc.) and therefore considered globally better.

One of the most characteristic multimodal functions used in lab problems are the Rastrigin function (see Fig. 1) which offers an excellent graphical point of view about multimodality means.

Providing multiple optimal (and valid) solutions and not only the unique global solution is crucial in multiple environments. Usually, it is very complex to implement in the practice the best solution represents, so it can offers multiple problems: computational cost too high, complex interpretation,…

In these situations it turns out useful to have a range of valid solutions between which that one could choose that, still not being the best solution to the raised problem, offer a level of acceptable adjustment and be simpler to implement, to understand, … that the ideal global one.

EVOLUTIONARY TECHNIQUES AND MULTIMODAL PROBLEMS

As it has been mentioned, the application of EC techniques to the resolution of multimodal problems sets out the difficulty that this type of techniques shows since they tend to solely provide the best of the found solutions and to discard possible local optimums that might have been found throughout the search. Quite many modifications have been included in the traditional performance of the GA in order to achieve good results with multimodal problems.

A crucial aspect when obtaining multiple solutions consists on keeping the diversity of the genetic population, distributing as much as possible the genetic individuals throughout the search space.

CLASSICAL APPROACHES

Nitching methods allow GAs to maintain a genetic population of diverse individuals, so it is possible to locate multiple optimal solutions within a single population.

In order to minimise the impact of homogenisation, or to tend that it may only affect later states of searching phase, several alternatives have been designed, based most of them on heuristics. One of the first alternatives for promoting the diversity was the applications of scaling methods to the population in order to emphasize the differences among the different individuals. Other direct route for avoiding the diversity loss involves focusing on the elimination of duplicate partial high fitness solutions (Bersano, 1997) (Langdon, 1996).

Some other of the approaches tries to solve this problem by means of the dynamic variation of crossover and mutation rates (Ursem, 2002). A higher amount of mutations are done in order to increase the exploration through the search space, when diversity decreases; the mutations decrease and crossovers increase with the aim of improving exploitation in optimal solution search when diversity increases. There are also proposals of new genetic operators or variations of the actual ones. For example some of the crossover algorithms that improve diversity and that should be highlighted are BLX (Blend Crossover) (Eshelman & Schaffer, 1993), SBX (Simulated Binary Crossover) (Deb & Agrawal, 1995), PCX (Parent Centric Crossover) (Deb, Anand & Joshi, 2002), CIXL2 (Confidence Interval Based Crossover using L2 Norm) (Ortiz, Hervás & García, 2005) or UNDX (Unimodal Normally Distributed Crossover) (Ono & Kobayashi, 1999).

Regarding replacement algorithms, schemes that may keep population diversity have been also looked for. An example of this type of schemes is crowding (DeJong, 1975)(Mengshoel & Goldberg, 1999). Here, a newly created individual is compared to a randomly chosen subset of the population and the most closely individual is selected for replacement. Crowding techniques are inspired by Nature where similar members in natural populations compete for limited resources. Likewise, dissimilar individuals tend to occupy different niches and are unlikely to compete for the same resource, so different solutions are provided.

Fitness sharing was firstly implemented by Goldberg & Richardson for being used on multimodal functions (Goldberg & Richardson, 1999). The basic idea involves determining, from the fitness of each solution, the maximum number of individuals that can remain around it, awarding the individuals that exploit unique areas of the domain. The dynamic fitness shar-

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