Chapter XIII
Genetic Algorithms and Multimodal Search

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ABSTRACT

Traditionally, the Evolutionary Computation (EC) techniques, and more specifically the Genetic Algorithms (GAs), 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. Most 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 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. The present chapter tries to establish, firstly, the characterisation of the multimodal problems will be attempted. A global view of some of the several approaches proposed for adapting the classic functioning of the GAs to the search of multiple solutions will be also offered. Lastly, the contributions of the authors and a brief description of several practical cases of their performance at the real world will be also showed.

INTRODUCTION

Following a general prospect, the GAs (Holland, 1975) (Goldberg, 1989) try to find a solution using a population: a randomly generated initial set of individuals. Every one of these individuals –who represent a potential solution to the problem-, will evolve according to the theories proposed by Darwin (Darwin, 1859) about natural selection and they will be more adapted to the required solution as generations pass.

Nevertheless, the traditional GAs find certain restrictions when the search space where they work has, either more than a global solution, or an unique global solution and multiple local optima. When faced with such scenarios, a classical GA tends to focalise the search on the environment of the global solution; however, it might be interesting to know the higher possible number of solutions due to different reasons: exact search space knowledge, implementation ease of local solutions compared with the global one, interpretation ease of some solutions compared with other ones, etc. To get this, an iterative process will be performed until the desired goals might be achieved. The process will start with the individuals grouping into species that will search independently a solution into their related environments. Following the later, the crossover operation will involve individuals of different species in order not to leave search space areas unexplored. The process will be repeated according to the achievement of the desired goals.

MULTIMODAL PROBLEMS

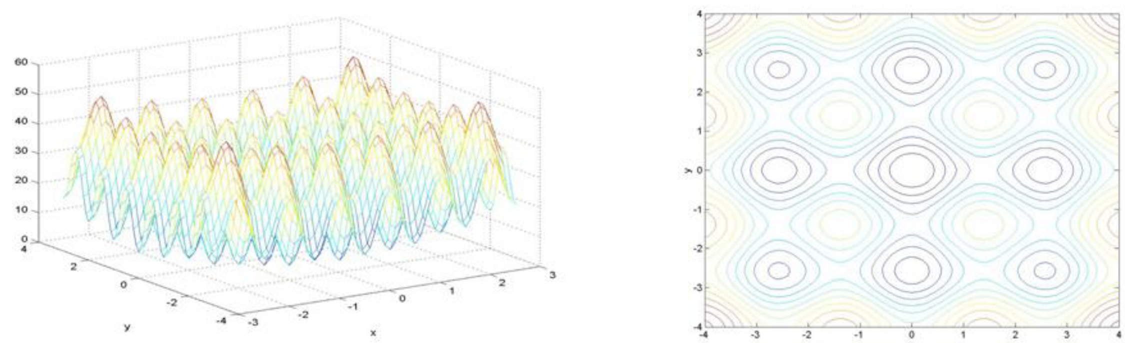
The multimodal problems can be defined as those problems that have either multiple global optima or multiple local optima (Harik, 1995).

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 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 not explored yet. On the other hand, although being certain that the best solution has been achieved, there might be other equally fitted or slightly worse 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 is the Rastrigin function (see Figure 1) which offers an excellent graphical point of view about what multimodality means.

Providing multiple optimal (and valid) solutions, and not only a unique global solution, is crucial in multiple environments. Usually, it is very

Figure 1. Rastrigin function: 3D and 2D representations



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