Hybrid Real-Coded Genetic Algorithms with Female and Male Differentiation

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Abstract- ***Parent-centric real-parameter crossover operators*** **create the offspring in the neighborhood of one of the parents,** ***the female parent,*** **using a probability distribution. The other parent,** ***the male one,*** **defines the range of this probability distribution. The** ***female and male differentiation*** **process determines the individuals in the population that may become female or/and male parents. An important property of this process is that it makes possible the design of two kinds of** ***real-coded genetic algorithms*****: ones that promote global search and ones that are effective local searchers. In this paper, we study the performance of a hybridization of these real-coded genetic algorithms when tackling the test problems proposed for the** ***Special Session on Real-Parameter Optimization of the IEEE Congress on Evolutionary Computation 2005.***

1 Introduction

The crossover operator has always been regarded as one of the main search operator in GAs, because it exploits the available information in previous samples to influence future searches. This is why most real-coded genetic algorithm (RCGA) research has been focused on developing effective real-parameter crossover operators, and as a result, many different possibilities have been proposed ([Deb01, Her98, Her03]). *Parent-centric crossover operators* (PCCOs) is a family of real-parameter crossover operators that has currently received special attention. In general, these operators use a probability distribution for creating offspring in a restricted search space around the region marked by one of the parent, the *female parent*. The range of this probability distribution depends on the distance between the female parent and the other parent involved in the crossover, the *male parent*.

So far, PCCO practitioners have assumed that every chromosome in the population may become either a female parent or a male parent. However, it is very important to emphasize that female and male parents have two differentiated roles:

- Female parents *point* at the search areas that will receive sampling points, whereas,
- Male parents are used to determine the *extent* of these areas.

At this point, it is reasonable to think that some chromosomes may be well-suited to act either as female parents or as male parents. Thus, a promising way to improve the behavior of PCCOs involves the introduction of a *female and male differentiation* (FMD) process for the application of these operators. A such process was proposed in [Gar05]:

- The population of the RCGA contains two different groups: 1) G_F with N_F chromosomes that can be female parents, and 2) G_M with N_M male parents (N_F and N_M are tunable parameters).
- The RCGA uses a specific selection mechanism in order to select the female parents from G_F.
- A different selection mechanism is performed to choose the male parents from G_M.

In [Gar05], it is indicated that adjusting N_F and N_M we may design *local* RCGAs, which offer *accuracy*, and *global* RCGAs, which provide *reliability*. Furthermore, in order to obtain robust behavior, in [Gar05], the authors combined a global RCGA and a local RCGA, producing a *hybrid* RCGA.

In this paper, this hybrid RCGA is tested on the test suite proposed for the *Real-Parameter Optimization Session of the IEEE Congress on Evolutionary Computation* ([Sug05]) (using the *Java* version provided to all participants).

We set up the paper as follows. In Section 2, we describe the pseudo-code of the hybrid RCGA. In Section 3, we presents the results obtained by this algorithm on the test suite when *Dimension=10*. The results with *Dimension=30* appear in Section 4. In Section 5, we study the computational costs of the algorithm, and, in Section 6, we list its associated parameters. In Section 7, we analyze the results obtained. Finally, we draw some conclusions in Section 8.

2 The Hybrid RCGA with the FMD Process

This section is aimed to introduce the hybrid RCGA. It consists on the hybridization of a global RCGA and a local RGGA. They are *steady-state* RCGAs based on a FMD process and that apply the replace worst strategy. In addition, the global RCGA uses the PBX-α crossover operator ([Loz04]) and the local RCGA uses the PCX crossover operator ([Deb02]).

In section 2.1, we describe the two PCCOs used by the algorithm. In section 2.2, the FMD process is introduced. Global and local RCGAs are presented in section 2.3.

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each function, seem similar to those ones when D = 10.

- *Global Optimum in the Initialization Range Vs Global Optimum outside of the Initialization Range* (Functions 24 and 25): When D = 10, the results for both functions are similar. Curiously, when D = 30, the results for function 24 deteriorate and those for function 25 are improved. We think that the algorithm is not affected by this characteristic.
- *Unimodal Functions* (Functions 1-5): When D = 10, the performance of the algorithm seems good in every function except for function 3. However, when D = 30, the performance deteriorates except for functions 1 and 2. It could be due to that the range of values of the fitness function 3, 4 and 5 is very wide.
- *Multi-modal Functions* (Functions 6-25): We think that the algorithm perform well on this type of problems, taking into account that other instances of the algorithm returned poorer results. In addition, the algorithm is not usually so much affect by the use of higher dimensions.
- *Functions with Global Optimum outside of the Initialization Range* (Functions 7 and 25): We think that the algorithm is able to go through the fitness landscape looking for the best regions. In [Gar05] the algorithm shows good results when using this kind of functions. In addition, it seems to perform well in the functions 7 and 25.
- *Functions with Global Optimum on Bounds* (Functions 5, 8 and 20): We think that function 8 is not a good one in order to measure the quality of an Evolutionary Algorithm, because, looking at the fitness landscape, there is no relation between the location of the global optimum and the information of the location of other solutions and their fitness values. So we will concentrate our comments on functions 5 and 20.

  The algorithm seems to be not affected by the location of the global optimum on bounds. The results for function 5 when D = 10 are very good. And it seems to perform well on function 20 when D = 10. However, when D = 30, the results for both functions deteriorate.

8 Conclusions

We have applied the hybrid RCGA presented in [Gar05] to the test suite for the Special Session on Real-Parameter Optimization of the IEEE Congress on Evolutionary Computation 2005. The results have let us to draw some characteristics of this algorithm when tackling problems with different properties.

For future works, we will be interested on improving this algorithm in order to increase the quality of its results for some type of functions, such as high conditioned functions, and to compare it with other algorithms on this test suite.

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