Components and Parameters of DE, Real-coded CHC, and G-CMAES

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Abstract

In this document, we provide the description of the instances of Differential Evolution (DE) [6], Real-coded CHC [3], and Restart Evolution Strategy with Increasing Population Size (G-CMA-ES) [1] that were used to evaluate the performance of the proposed algorithms for the Special Issue of Soft Computing on Scalability of Evolutionary Algorithms and other Metaheuristics for Large Scale Continuous Optimization Problems.

1 Differential Evolution

We have considered a classic DE model, with no parameter adaptation, at all. The crossover operator applied was *rand/1/exp*. We have observed that the results obtained on the test suite by using the *rand/1/exp* operator are clearly better than the ones obtained by employing the *rand/1/bin* operator, which is another well-known crossover operator for DE (the results of DE with these two operators may be found in `http://sci2s.ugr.es/eamhco/decross_values.xls`). The F and CR parameters were fixed to 0.5 and 0.9 values, respectively.

An important decision for the application of DE to large scale problems is the choice of the population size (*popsize*). Usually, this parameter is set in function of the problem dimension ($10 \cdot D$ or $3 \cdot D$). When DE tackles functions with high dimensionality ($500-1000$), this criterion is not adequate, and a maximum limit should be fixed. For the experiments, a population of 60 individuals was used (we have analyzed DE with $popsize = 100$ and similar results were achieved).

2 Real-coded CHC

The key idea of the CHC algorithm (Crossgenerational elitist selection, Heterogeneous recombination, and Cataclysmic mutation) [2] concerns the combination of a selection strategy with a very high selective pressure and several

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components inducing a strong diversity. The CHC algorithm was tested against different genetic algorithm approaches, giving better results, especially on hard problems [7]. So, it has arisen as a reference point in the genetic algorithm literature. In [3], the original CHC model was extended to deal with real-coded chromosomes, maintaining its basis as much as possible.

Real-coded CHC is based on the same four main components than classical CHC. The elitist selection is exactly the same in both cases. In order to apply the heterogeneous recombination, the real values of the two individuals' parameters are encoded into bit strings using binary reflected Gray coding and the Hamming distance between the parents is measured. Only those string pairs which differ from each other by some number of bits (*mating threshold*) are mated. The initial threshold is set at $\frac{L}{4}$, where L is the length of the string ($L = 20 \cdot D$ in the experiments). When no offspring are inserted into the new population the threshold is reduced by 1. When the population converges or the search stops making progress (i.e., the difference threshold has dropped to zero and no new offspring are being generated which are better than any members of the parent population), the population is reinitialized. The restart population consists of random individuals except for one instance of the best individual found so far. Finally, a real-parameter crossover operator, called BLX-α [3], is considered to substitute the original crossover operator. The instance of real-coded CHC uses BLX-α with $\alpha = 0.5$ and the population size is 50 chromosomes.

3 G-CMA-ES

G-CMA-ES is a restart Covariant Matrix Evolutionary Strategy (CMA-ES) with Increasing Population Size [1]. This CMA-ES variation detects premature convergence and launches a restart strategy that doubles the population size on each restart; by increasing the population size the search characteristic becomes more global after each restart, which empowers the operation of the CMA-ES on multi-modal functions. G-CMA-ES was the winner of the real-parameter optimization competition, organized in the 2005 IEEE congress on evolutionary computation (CEC2005) (as recognized in [5] and [4]).

The values considered for the G-CMA-ES parameters were the ones suggested by Auger and Hansen [1]. The initial solution is uniform randomly chosen from the domain and the initial distribution size (σ) is a third of the domain size.

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