Adaptive Meta-Lamarckian Learning in Hybrid Genetic Algorithms

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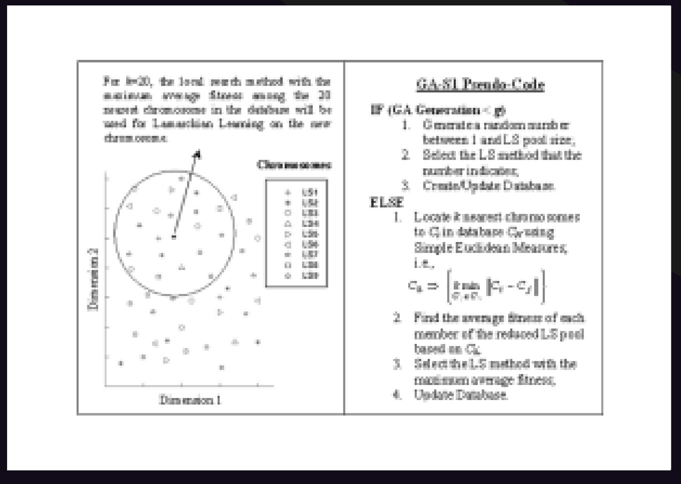
We present strategies for hybrid Genetic Algorithm-Local Searches (GA-LS) control that decide, at runtime, which local method from a pool of different local methods, is chosen to locally improve the next chromosome. The use of multiple local methods during a hybrid GA-LS search in the spirit of Lamarckian learning is termed Meta-Lamarckian Learning. Two adaptive strategies are studied on the Griewank test function. The proposed approach is shown to yield robust and improved design search performance.

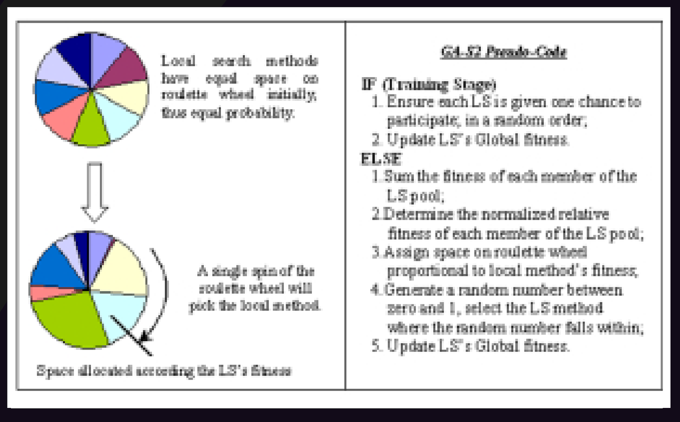
Adaptive Meta-Lamarckian Learning

Inspired by the research works on different kinds of effort in social evolution, two adaptive strategies of Meta-Lamarckian learning in hybrid GA-LS are structured to promote cooperation and competition among the different LSs, working together to accomplish the shared optimization goal.

Two Cooperation and Competition Adaptive Meta-Lamarckian Strategies



A Heuristic Approach, Sub-problem Decomposition – GA-S1



A Stochastic Approach, Biased Roulette Wheel – GA-S2

Experimental Studies

The basic steps of the hybrid GA-LS search with Meta-Lamarckian Learning are outlined below:

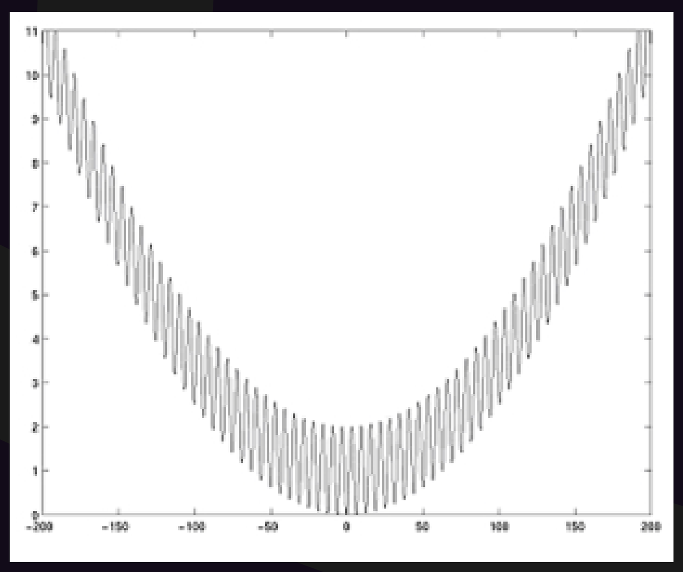
BEGIN
Initialize: Generate an initial GA population.
While (Stopping condition are not satisfied)
  Evaluation of All Individuals in the Population
    For each individual in the population
      • *Select LS using the Meta-Lamarckian Learning Strategy employed and proceed with local improvement.*
      • *Reward/Update fitness of selected local search method.*
      • *Replace the genotype in the population with the locally improved solution.*
      } **Pseudo-code of GA-S1 or GA-S2 comes in here**
    End For
    Apply standard GA operators to create a new population; i.e., Selection, Mutation and Crossover.
  End While
END

Algorithm for Hybrid GA-LS With Meta-Lamarckian Learning

Experimental Results On Griewank Benchmark Test Problem

Griewank function is a multimodal function with many local minima and a global minimum located at (0,...,0). It has a very rugged landscape and is given by:

$$F_{Griewank} = 1 + \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \left[\cos\left(x_i / \sqrt{i} \right) \right]$$

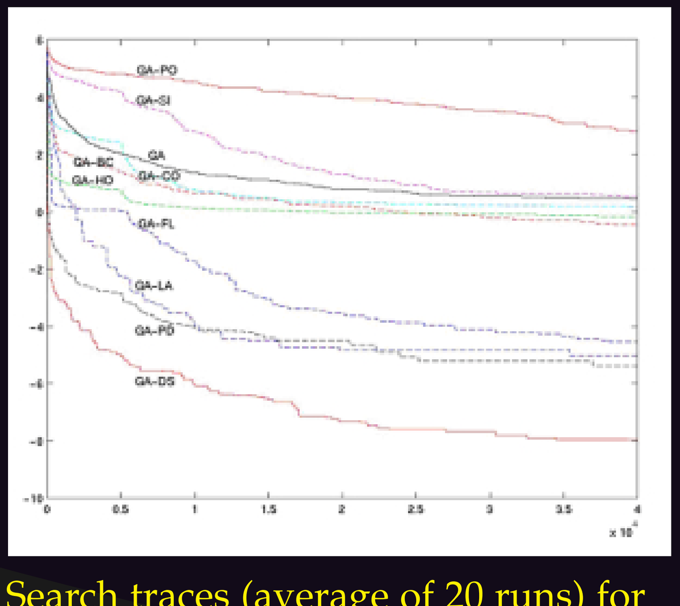


One-dimensional slice of the Griewank function for [-200, 200]10.

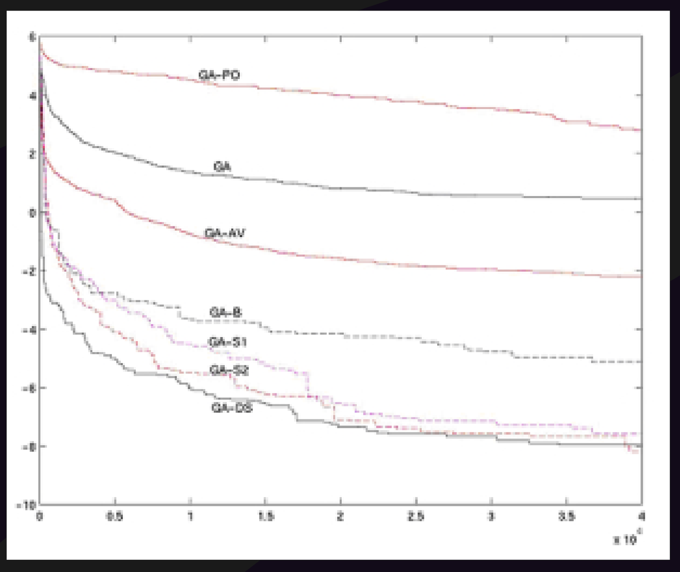
A variety of constrained and unconstrained nonlinear local search methods were employed in the study. Nine hybrid GA-LSs are presented here: GA-BC, GA-CO, GA-DS, GA-HO, GA-FL, GA-LA, GA-NM, GA-PD and GA-PO. These abbreviations have the following meanings:

GA: Standard GA;
GA-BC: GA with Bit Climbing Algorithm by Davis;
GA-CO: GA with Complex Method of M.J.Box as implemented by Schwefel;
GA-DS: GA with Davies, Swann and Campey Search with Gram-Schmidt orthogonalization as implemented by Schwefel;
GA-HO: GA with Hooke and Jeeves Direct Search by Siddall;
GA-FL: GA with Fletcher's 1972 method by Siddall;
GA-LA: GA with Repeated Lagrangian Interpolation as implemented by Schwefel;
GA-NM: GA with Simplex Method by Nelder and Meade;
GA-PD: GA with Powell's Direct Search Method as produced by AERE Harwell;
GA-PO: GA with Powell's Direct Search Method [27] as implemented by Schwefel;
GA-B: This represents the estimated performance one might expect to get when the selection of a fixed LS from the entire pool for GA hybrid is made randomly;
GA-AV: This is an average of the performances for the entire pool of nine fixed LS hybrids on a problem.

The convergence trends of the various local methods in GA hybrid are shown in the figure. It is evident how the choice of the local search method employed greatly effect the efficiency of problem searches. The most appropriate local search method for the Griewank function is shown to be GA-DS hybrid.



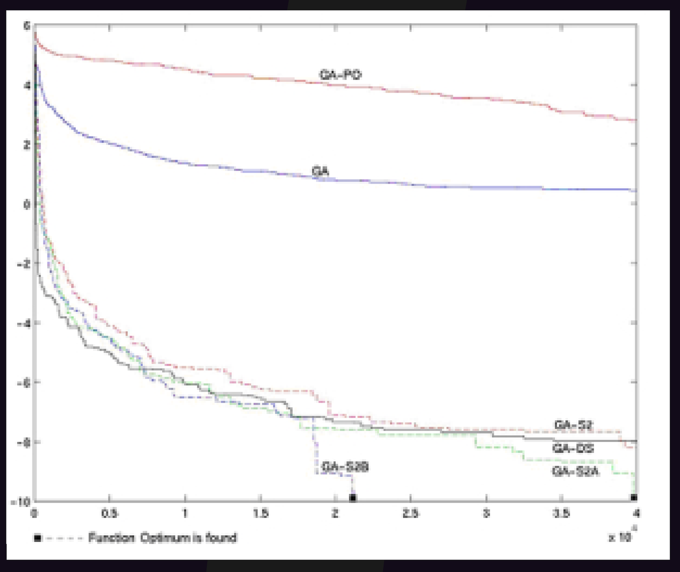
Search traces (average of 20 runs) for minimizing 10D Griewank function using the nine local search methods.



Search traces (average of 20 runs) for minimizing 10D Griewank function using the Adaptive Meta-Lamarckian Strategies, i.e., Traces GA-S1 and GA-S2.

The convergence trends for the various adaptive strategies of Meta-Lamarckian learning when applied on the Griewank function is as shown in the figure. It is seen that both adaptive strategies, GA-S1 and GA-S2, were able to correctly select the most appropriate local search method for the Griewank function, thus displaying performances close to GA-DS.

The other great advantage of the adaptive Meta-Lamarckian GA-LS strategies is that further improvement of search performance further search may be attained when human designer knowledge is incorporated into the search. Trace GA-S2A illustrates the case where the DS method is biased with twice the chances of being selected, as compared to the other local methods in the same pool. Trace GA-S2B is obtained when the designer chooses to use six local methods (PO, NM, CO, BC, PD and DS) as the pool to perform a search on the Griewank function. It is seen that superior search performances are obtained over the most appropriate local method, GA-DS.



Search traces (average of 20 runs) for minimizing 10D Griewank function using the Adaptive Meta-Lamarckian Strategies with the incorporation of Human Designer Knowledge, i.e., Traces GA-S2A and GA-S2B.

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