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AN ANALYSIS OF A HYBRID EVOLUTIONARY ALGORITHM BY MEANS OF ITS PHYLOGENETIC INFORMATION

ANTONIO LATORRE, SANTIAGO MUELAS AND JOSÉ-MARÍA PEÑA
DATSI, Facultad de Informática, Universidad Politécnica de Madrid
Campus de Montegancedo S/N, 28660, Boadilla del Monte, Madrid, ESPAÑA
{atorre, smuelas, jmpena}@fi.upm.es

ABSTRACT— The study conducted in this work analyses the interactions between different Evolutionary Algorithms when they are hybridized. For this purpose, the phylogenetic tree of the best solution reported by the hybrid algorithm is reconstructed, and the relationships among the ancestors of this solution are established. For each of these ancestors, the evolutionary techniques that generated that solution and the fitness increment introduced compared to its parents are recorded. The study reveals a structured interaction among the different evolutionary techniques that makes the hybrid algorithm to outperform each of its composing algorithms when executed individually. The Multiple Offspring Sampling framework has been used to develop the Hybrid EA studied in this work and the experiments have been conducted on the well-known CEC 2005 Benchmark for continuous optimization.

Key Words: Evolutionary Algorithms, Hybridization, Multiple Offspring Sampling, Phylogenetic Information

1. INTRODUCTION

In the recent years, there have been several studies trying to analyze the dynamics of Evolutionary Algorithms (EAs) [1,2]. Among these studies, it's worth noting the work of Whitacre et al. [3], in which the authors try to exploit the phylogenetic information stored during the search to analyze the influence of each individual in the dynamics of the algorithm. The analysis conducted in this work uses a somehow different approach. On the one hand, this study focuses on the interaction of different EAs when they are hybridized and used simultaneously. On the other hand, the study considers the best individual reported by the hybrid algorithm and backwards reconstructs its genealogical tree from the relationship between parent and child individuals. The objective is to try to explain why a hybrid algorithm would perform better than any of its components. Much work has been done in the field of Hybrid EAs, but few of them analyzed the reasons for this increase performance. In [4] several alternatives for adjusting the participation of each evolutionary technique making up a hybrid algorithm are compared, concluding that an intelligent adjustment strategy always obtains better results than a naïve one (the use of constant participation ratios, for example). Now, the idea is to study how these intelligent strategies actually work and to find patterns of behavior that could be used to improve even more the performance of Hybrid EAs.

2. MULTIPLE OFFSPRING SAMPLING

The Multiple Offspring Sampling (MOS) framework [5] provides the necessary tools to develop Hybrid Dynamic Evolutionary Algorithms capable of handling several evolutionary approaches simultaneously and of dynamically adjusting the participation of each of them in the overall search process. The Algorithm 1 presents a pseudocode of a hybrid algorithm developed with MOS.

In MOS, the hybrid algorithm handles the mechanisms to produce new individuals belonging to the different evolutionary approaches (recombination operators in GAs, probabilistic models in EDAs, etc.). Each of these mechanisms capable of producing a new offspring is called a *technique*. Specifically, a technique can be defined as: (a) a particular evolutionary model, (b) with an appropriate encoding, (c) using specific operators (if needed), and (d) configured with its necessary parameters.

Each of these techniques is able to produce a subset of the offspring from the current population, which is shared by all the techniques. The number of individuals that each technique can generate at each generation ($\Pi_i^{(j)}$) is called its participation ratio. This ratio is uniformly distributed at the beginning of the search process, and is periodically updated according to a given policy. In the canonical version of MOS, this adjustment is carried out by what is known as a *Participation Function (PF)*. This function can carry out simple static assignments or, more interestingly, dynamic adjustments according to a *Quality Measure* that evaluates how good the offspring of each technique is from the point of view of that measure ($Q_i^{(j)}$).

1: Create initial overall population of candidate solutions P_0
2: Uniformly distribute participation among the n used techniques $\rightarrow \forall j\ \Pi_0^{(j)} = \frac{|P_0|}{n}$. Each technique produces a subset of individuals according to its participation ($\Pi_0^{(j)}$)
3: Evaluate initial population P_0
4: **while** termination criterion not reached **do**
5:     Update Quality of $T_j \rightarrow Q_i^{(j)} = Q(O_{i-1}^{(j)}), \forall j$
6:     Update participation ratios from Quality values computed in Step 5 $\rightarrow \forall j\ \Pi_{i+1}^{(j)} = PF(Q_i^{(j)})$
7:     **for** every available technique T_j **do**
8:         **while** ratio $\Pi_i^{(j)}$ not exceeded **do**
9:             Create new individuals from current population P_i using technique T_j
10:             Evaluate new individuals
11:             Add new individuals to an auxiliary offspring population $O_i^{(j)}$
12:         **end while**
13:     **end for**
14:     Combine populations $O_i^{(j)}\ \forall j$ and P_i according to a pre-established criterion to generate P_{i+1}
15: **end while**

Algorithm 1 Pseudocode of a Hybrid EA developed with MOS

In this work, the Dynamic Participation Function presented in Equation 1 has been used. This PF evaluates, at each generation, the quality of the offspring produced by each technique. Then, each technique has its participation decreased by a trade-off factor $\Delta_i^{(j)}$, which is computed from the relative quality difference between that technique and the best one. The best technique has its participation increased by the sum of all these $\Delta_i^{(j)}$ factors.

$$PF_{dyn}(O_{i-1}^{(j)}) = \begin{cases} \Pi_{i-1}^{(j)} + \sum_{k \neq best} \Delta_i^{(k)} & if\ j = best, \\ \Pi_{i-1}^{(j)} - \Delta_i^{(j)} & otherwise \end{cases}$$

$$\Delta_i^{(j)} = \xi \frac{Q(O_{i-1}^{(best)}) - Q(O_{i-1}^{(j)})}{Q(O_{i-1}^{(best)})} \Pi_{i-1}^{(j)} \quad \forall j \in [1, n] / j \neq best$$

Equation 1 Dynamic Participation Function

To compute the quality of the offspring associated to each technique, the average fitness of the top ρ percent of the offspring populations is calculated, as depicted in Equation 2.

$$Q(O_i^{(j)}) = fAvg(O_i^{(j)}, \rho)$$

Equation 2 Average Fitness Quality Measure

This way, the Hybrid EA will not only combine the different search capabilities of several evolutionary techniques, but also dynamically adjust the participation of each of them according to their current performance.

On the other hand, for each new individual created by one of the available reproductive technique, its parents and the technique it was created with will be recorded. This way, the phylogenetic analysis proposed in the next section could be carried out.

3. PHYLOGENETIC INFORMATION

To analyze the behavior of a Hybrid EA from the point of view of the interaction of the different evolutionary techniques collaborating in the search, one option is to reconstruct the genealogical tree of the best individual reported by the algorithm at the end of its execution. From this individual, all its ancestors back until the first generation will be identified, and the relationships among them will be established. For each of the ancestors, its associated technique (the one used to create that individual) and the fitness increment compared with the best of its ancestors are recorded. With that information, a genealogical tree similar to the one depicted in Figure 1 can be constructed.

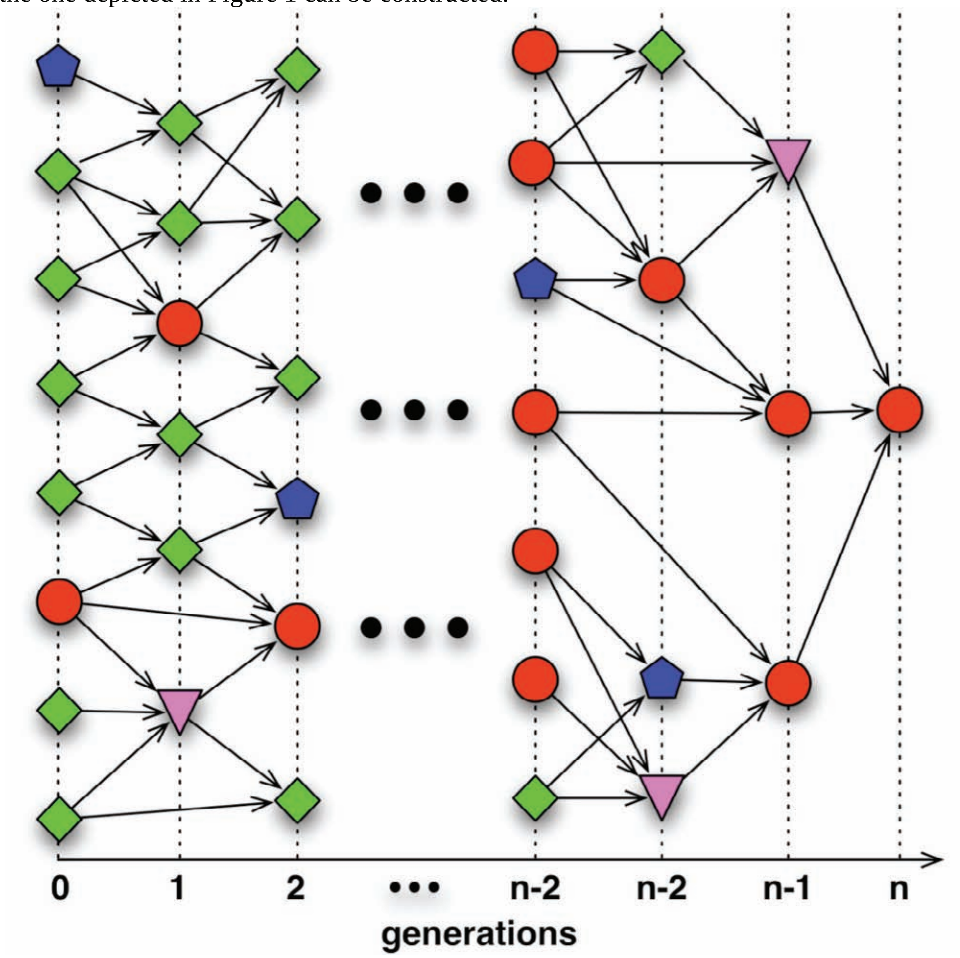

Figure 1 Example of a phylogenetic reconstruction from the best individual

In this figure, each individual is represented with a different shape and color depending on its associated creation technique, and the relationships between the ancestors are also shown. This information will be used in the following experimentation to see if patterns of interaction between different techniques can be established. The number of direct ancestors (parents) of one individual depends on which technique is being used (2 parents for GAs and 4 for DE).

4. EXPERIMENTATION

For this experimentation, the well-known CEC 2005 Benchmark for continuous optimization [6] has been used. This benchmark is made up of 25 continuous functions of different complexity. The hybrid algorithm used for the experiments has been configured with four techniques: two Genetic Algorithms (BCGM and UCUM) and two Differential Evolution algorithms (DE Exponential and DE Binomial). These techniques have been selected for the good results obtained with their combination in a preliminary experimentation [5]. The particular configuration of each of the techniques is detailed in Table I (a).

Table I (a) Configuration of the techniques and (b) Configuration of the hybrid algorithm

	BCGM	UCUM
Selector	Tournament (size 2)	Uniform
Initializer	Uniform	
Crossover	BLX-α (α = 0.5)	Uniform
Mutator	Gaussian	Uniform
Crossover %	90%	
Mutation %	10%	

Executions	25
Dimensionality	10
Population Size	100
Stop Criterion	100,000 Fit. Evals.
Elitism	Full Elitism
Minimum Participation	0%
Quality Measure	Average Fitness

Besides, the global configuration for the hybrid algorithm can be found in Table I (b). Most of the parameters in both Tables I (a) and (b) have been obtained either in a preliminary experimentation or they are classic in the literature. Regarding the hybridization procedure itself, a Dynamic Participation Function has been used. In this case, it uses the Average Fitness of the new individuals created by each technique. A minimum participation ratio of 0% was established. This means that any technique which quality is poor for a long number of generations could be eventually discarded and stop producing new individuals.

As the experimental results are too extensive to be detailed in this paper, a summarized version is provided in Table II. This table presents, on the first hand, the average ranking on the 25 functions that make the benchmark up. It can be observed that the average ranking obtained by the hybrid algorithm developed with MOS is much better than any of its composing algorithms. On the other hand, the Holm Procedure has been used to assess the statistical significance of the results. This procedure allows the comparison of multiple algorithms taking the Family-Wise Error into account, as described in [7]. For this purpose, the algorithm with the best average ranking (the MOS Hybrid in this case) is taken as the control algorithm for the subsequent comparisons. This algorithm will be statistically compared against each of the other algorithms, reporting if there are significant differences between them. In this case, the Holm Procedure found significant differences between the MOS Hybrid algorithm and all the other algorithms, with a significance level α = 0.05.

Table II Average Ranking on the 25 functions and results of the Holm Procedure

	Average Ranking	Holm Procedure
MOS Hybrid	1.74	—
DE Exponential	2.68	✓
DE Binomial	3.30	✓
BCGM	3.44	✓
UCUM	3.84	✓

Regarding the phylogenetic study, two measures will be analyzed for each of the considered functions. First, the percentage of ancestors of the best final individual produced by each technique at each generation will be plotted. This figure will be compared with the dynamic adjustment of participation carried out by the algorithm according to the selected quality measure. And second, the fitness increment introduced in the population by each technique at each generation will be also considered. This will allow an analysis of which influence each of the techniques actually had on the best final solution: if it helped to explore the solutions space or if it was able to refine current solutions and increase their fitness value.

Figure 2 (left) presents the evolution in the number of ancestors of the best final individual by the technique that created each of the ancestors for function F2 (Shifted Schwefel's Problem 1.2). It can be seen that the percentage of ancestors created by the first GA technique (the BCGM technique) dominates during the first 100 generations. This seems to contrast with the participation adjustment depicted in Figure 2 (right). In that figure, the DE Exponential technique acquires most of the participation. Looking at the Quality Measure plot (Figure 3 left) it can be seen that none of the algorithms is actually creating good individuals (in average), although the individuals created by the DE Exponential are better (it can not be seen in the plot due to the low scale of the fitness values at that point). However, during those generations the BCGM is creating more diverse solutions that help the hybrid algorithm to explore the solutions space (although their fitness values are not very good, in average).

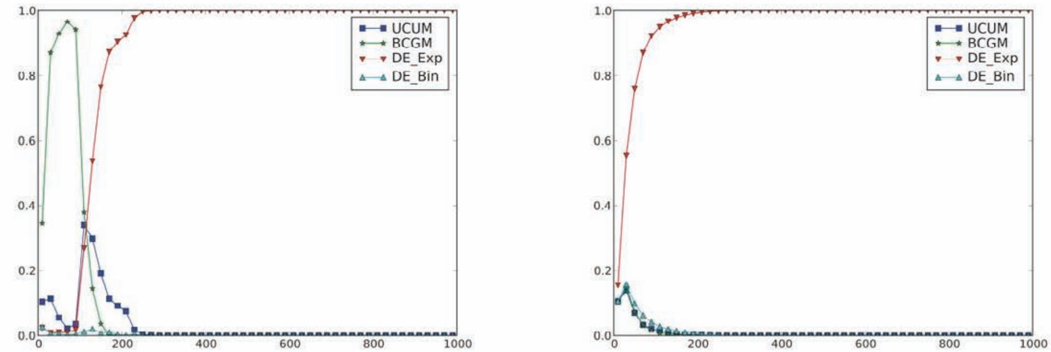

Figure 2 Percentage of ancestors for each technique (left) and participation adjustment (right) for F2

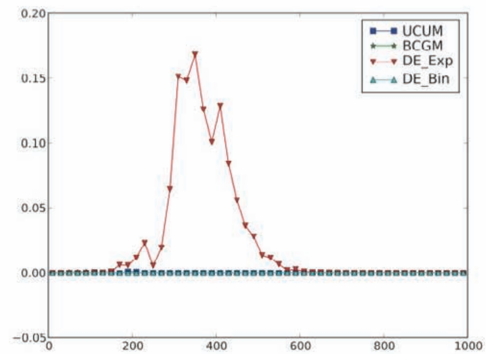

Figure 3 Quality (left) and Fitness Increment (right) evolutions for F2

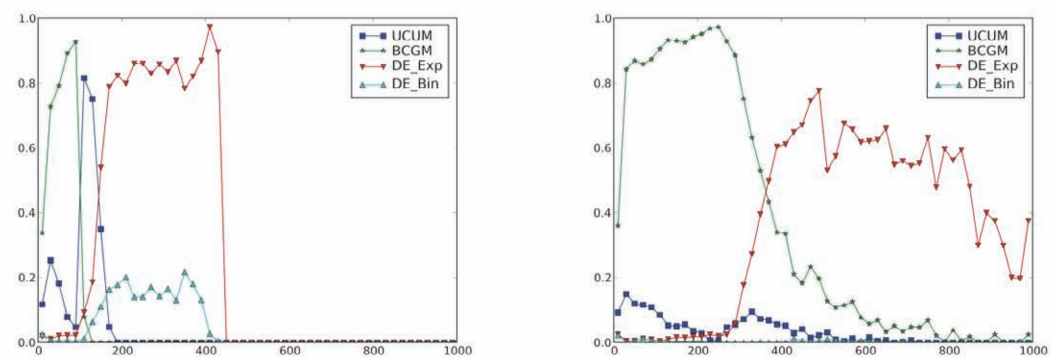

Figure 4 Percentage of ancestors for each technique in functions F9 (left) and F22 (right)

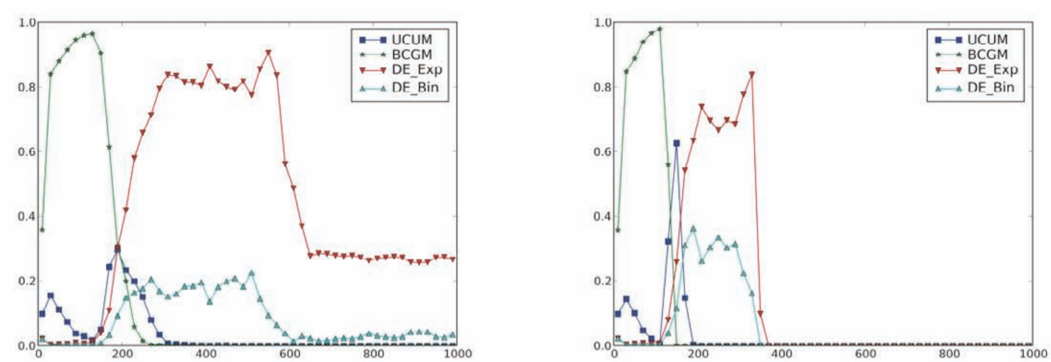

Figure 5 Percentage of ancestors for each technique in functions F18 (left) and F24 (right)

From generation 100 on, the DE Exponential technique takes over and it is able to refine the solutions found by the BCGM technique. This behavior can be observed in Figure 3 (right), which plots the fitness increments introduced by each technique during the execution of the algorithm. It can be seen that during the first generations, in which the BCGM technique had more influence on the final best individual, the increments in fitness were really low, as the algorithm was exploring the solutions space. From around generation 200, the DE Exponential algorithm is able to refine the solutions found by the BCGM technique, especially during generations 300 to 400. This function was selected for the analysis because the hybrid algorithm was able to reduce six orders of magnitude the relative error compared with the best individual technique (the DE Exponential).

A similar behavior can be observed in most of the remaining functions: the BCGM technique has a higher influence on the final solution during the first generations (due to its exploration capabilities) and the DE Exponential refines the solutions found by the BCGM technique. However, some differences arise depending on the particular function. For example, in some cases the BCGM phase lasts for a larger number of generations, as in Figure 4 (left). In other cases, the UCUM technique helps the hybrid algorithm to better explore the solutions space, once the BCGM has got stuck (Figure 4 right). Finally, the participation of the DE Binomial algorithm is constrained to a limited number of functions, although in those cases it helps the hybrid algorithm not to be misleaded by the other algorithms (Figure 5 left and right).

5. CONCLUSIONS

In this paper, an analysis of the dynamics of a Hybrid EA has been presented. For this purpose, the phylogenetic information retrieved from the reconstruction of the genealogical tree of the best individual has been used. The study has been conducted on a well-known benchmark for continuous optimization in which a Hybrid EA is able to outperform each of its composing algorithms with statistical significance. The study revealed a clear pattern of interactions between the different evolutionary techniques that leaded to this increased performance. In the future, this information could be used to train controllers to carry out a better dynamic adjustment of the participation of different evolutionary techniques.

6. ACKNOWLEDGMENTS

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