Combining Incest Prevention and Multiplicity in Evolutionary Algorithms

Minetti G., Salto C., Alfonso H.
Proyecto UNLPAM-09/F009[1]
Departamento de Informática - Facultad de Ingeniería
Universidad Nacional de La Pampa
Calle 110 esq. 9
(6360) General Pico – La Pampa – Rep. Argentina
e-mail: {minettig,saltoc,alfonsoh }@ing.unlpam.edu.ar;

Gallard R.
Proyecto UNSL-338403[2]
Departamento de Informática
Universidad Nacional de San Luis
Ejército de los Andes 950 - Local 106
(5700) - San Luis – Rep. Argentina
e-mail: rgallard@unsl.edu.ar

Abstract

Evolutionary Computation is an emergent field, which provides new heuristics to function optimization where traditional approaches make the problem computationally intractable.
Exploration and exploitation of solution in the problem space are main issues affecting the performance of an evolutionary algorithm. Current enhancements attempt to balance exploitation and exploration to avoid premature convergence during the search process.
Multiple parents multiple crossovers and incest prevention are three different techniques that when combined showed a substantial benefit: besides minimizing the risk of premature convergence, the final population is concentrated nearby the optimal solution.
This behaviour is an important aid provided by the evolutionary process when applications require a set of alternative solutions to face system dynamics.
This paper shows the design, implementation and partial performance results when incest prevention is combined with multiple crossovers on multiple parents for difficult multimodal optimization.

Keywords: Genetic Algorithms, Multiple Crossovers, Multiple Parents, Incest Prevention, Scheduling, Cluster Allocation.

[1] The Research Group is supported by the Universidad Nacional de La Pampa.
[2] The Research Group is supported by the Universidad Nacional de San Luis and the ANPCYT (National Agency to Promote Science and Technology).

1. Introduction

In the case of multimodal functions the problem space, also known as the *fitness landscape*, provides multiple suboptimal points. Depending on the type of operators used and their frequency of application, the convergence to these suboptimal points can arise. This effect, known as *premature convergence*, is mainly derived from a loss of population diversity before optimal, or at least satisfactory values, have been found.
When searching for optimal solutions in the problem space extreme exploitation can lead to premature convergence but intense exploration can make the search ineffective [Michalew. 96].

Multiple crossovers per couple (MCPC) was recently introduced as a new crossover method [Esquivel 97] attempting higher exploitation of previously found solutions. Allowing multiple crossovers per couple on a selected pair of parents provided an extra benefit in processing time and similar quality of solutions when contrasted against the conventional approach, which applies a single crossover operation per couple. These results, were confirmed when optimising classic testing functions and harder (non-linear, non-separable) functions.

Despite the above mentioned benefits, due to a reinforcement of selective pressure, MCPC showed in some cases an undesirable premature convergence effect and some adjustment were needed. Focussing on the exploitation versus exploration equilibrium problem, a previous proposal combined MCPC with an alternative selection method; Fitness Proportional Couple Selection (FPCS) which first, creates an intermediate population of couples where both individuals were chosen by proportional selection. Then a criterion is applied to establish the fitness of a couple and subsequently, couples are selected for crossing-over based on couple fitness [Esquivel 98].

Also recently, Eiben [Eiben 94], [Eiben 95], [Eiben 97-1], [Eiben 97-2], proposed a *multiparent approach*, where offspring creation is based on a larger sample from the search space attempting to supply larger diversity in the population. Diversity can help to avoid premature convergence.

Eshelman and Shaffer [Eshelman 91], under a different view proposed *incest prevention*, which also showed its benefits to avoid premature convergence. The method avoided mating of pairs showing similarities based on the parent’s hamming distance.

In a previous work we showed an *extended approach of incest prevention* by maintaining information about ancestors within the chromosome and modifying the selection for reproduction in order to prevent mating of individuals belonging to the same “family”, for a predefined number (1 to 3) of generations. This novel approach was tested on a set of multimodal functions. Description of experiments and analyses of improved results can be seen in [Alfonso 98].

Lately, extending the Eiben’s multiparent proposal in a Pareto optimality study, we found that good results can be obtained by applying *multiple crossovers per mating action* (MCPMA), a natural extension of MCPC, on multiple parents [Esquivel 99-1]. Encouraged by these results an investigation was conducted to establish the raw effect in performance on a pair of selected optimization problems by using a new *multiple crossovers on multiple parents* (MCMP) method, which allows multiple recombination of multiple parents under *uniform scanning crossover*. Results under MCMP were better in quality and speed of convergence than previous approaches attempting improvements of MCPC and were published elsewhere [Esquivel 99-2]

The present work indicates that allowing multiple crossovers between multiple parents preventing incest, improve the search process in an evolutionary algorithm.
Next sections briefly describe the method experiments and analyses of improved results on two hard multimodal functions (Griewank’s and Branin’s Rcos).

2. Multiple crossovers on multiple parents (MCMP)

Here we explain our *multiplicity approach* expressed as multiple mating of multiple contributing parents. In his preliminary *multiparent approach* Eiben used, three scanning crossover methods; but the most promising was uniform scanning crossover. Here, each gene in the child is provided from any of the corresponding genes in the parents with equal probability. By using a greater number n_1 of parents, offspring creation is based on a larger sample from the search space and consequently larger diversity is supplied. This can help to avoid premature convergence. As reported in Eiben's work, it was difficult to draw conclusions on the optimal number of parents, but it was determined that a better performance is attained when 2 to 4 parents are used and increasing the number of parents could deteriorate the performance.

Multiple crossovers on multiple parents (MCMP), the method used here, allows multiple recombination of multiple parents under uniform scanning crossover, expecting that exploitation and exploration of the problem space be adequately balanced.

As an extension of MCPC, MCPMA provides a means to exploit good features of more than two parents selected according to their fitness by repeatedly applying the selected crossover method (in this case uniform scanning). Once selected, the parents undergo crossover a number n_2 of times specified as an argument, and generates n_2 children (one per crossover operation).

3. General description of extended incest prevention (EIP)

In EIP the concept of incest is highly related to the concept of mating members of the same family. To prevent incest EIP allows only recombination of individuals without common ancestors. To build the new population in EIP, individuals are randomly chosen from the previous one according to the conventional *fitness proportional selection*, but they are allowed to crossover only if no common ancestors are detected in earlier generations. In this way exchange of similar genetic material is reduced and population diversity is maintained up to some convenient degree. Persistent high population diversity has also a detrimental effect slowing down the search process.

To make this point clearer we have to notice that by allowing crossover only on some *non*-relative individuals, we modify the effect of the selection mechanism on the population. Moreover, selection is the only operator of an EA where the fitness of an individual affects the evolution process. In such a process two important, strongly related, issues exist: population diversity and selective pressure enforced by the mechanism. They are the sides of the same coin: exploration of the searching space versus exploitation of information gathered so far. Selection plays an important role here because strong selective pressure can lead to premature convergence and weak selective pressure can make the search ineffective.

In this work we address the issue by fixing the number of generations to determine the ancestry relationship between individuals. The following pseudo-code delineates a procedure to prevent incest between members of the same or consecutive generations (brother-sister and parent-offspring) when only two parents are involved.

```
procedure parent selection
  begin
   for 1 to sizepop
     select indiv-1 C(t) //C(t) previous generation
     select indiv-2 C(t)
     while  ((parent(indiv-1)=parent(indiv-2)) OR
              (indiv-1=parent(indiv-2)) OR
              (indiv-2=parent(indiv-1)))
           select indiv-2 C(t)
     end while
     recombine and mutate individuals in C(t) building C'(t);//C'(t) next generation
  end for
  end
```

When a number of $n_1 > 2$ parents are used, the above pseudo code is modified as follows.

```
procedure multiple  parent selection
begin
    int mating_pool[cant_parents]  //array to store selected parents//
    int children_pool[cant_cross]   //array to store created offspring//
    for 1 to popsize
        select indiv-1 C(t)
        mating_pool[1] = indiv-1
        i=2
        while (i <= cant_parent)
            repeat
                select indiv-i C(t)
            until(is_relative(mating_pool, indiv-i)) // control of no common          ancestry
            and uniqueness of parents in the mating pool//
            matting_pool[i] = indiv-i
            i=i+1
        end while
        recombine using MCPMA and mutate individuals from mating_pool to
                                                        children_pool
        select the best individual from children_pool building C'(t)
    end for
end procedure
```

As can be observed when MCPMA and bit flip mutation is applied, obtaining n_2 offspring, a subsequent selection choose the fittest child for insertion in the next generation.

4. Experiments description

For this report, we choose contrasting results on two multimodal functions of varying difficulty:

***f1*:** Griewangk's Function

$$f_1(x_i) = 1 + \sum_{i=1}^{5} \frac{x_i^{\,2}}{4000} - \prod_{i=1}^{5}\left(\cos\left(\frac{x_i}{\sqrt{i}}\right)\right),$$

$$x_i = -600:600\ , i = 1:5;$$

$$\text{minimum global value}:\ 0.0$$

***f2*:** Branins's Rcos Function

$$f_4(x_1, x_2) = \left(X_2 - \frac{5.1}{(4\cdot\pi^2)}\cdot x_1^{\,2} + \frac{5}{\pi}\cdot X_1 - 6\right)^2 + 10\cdot\left(1-\frac{1}{(8\cdot\pi)}\right)\cdot\cos(x_1)+10,$$

$$x_1 = -5:10,\quad X_2 = 0:15;$$

$$\textit{minimum}\ \text{global value}:\ 0.397887$$

When optimizing the above indicated functions the following experiments were performed:

1. Multiple Parents (MP)
2. Multiple Parents with Incest Prevention (MPIP)
3. Multiple Crossover on Multiple Parents (MCMP)
4. Multiple Crossover on Multiple Parents with Incest Prevention (MCMPIP).

EIP was implemented as above described, carrying the ancestors history to prevent incest of individuals with common ancestors in the last two consecutive generations.

To obtain experimental results series of many runs, each with randomised initial population, were performed for each experiment on each function, using proportional selection, binary coded representation, elitism, uniform scanning crossover and bit flip mutation.
For those experiments without incest prevention the population size was fixed to 70 individuals. When incest prevention was implemented, in order to find subsets of n_1 parents for mating with no common ancestors, the size of the population was augmented to 170 individuals.
The number of generations was fixed to 500 and probabilities for crossover and mutation were fixed to 0.5 and 0.005 for *f1* and *f2*.

As an indication of the performance of the algorithms the following relevant performance variables were chosen:

Ebest = (Abs(*opt_val* - best value)/*opt_val*)100
It is the percentile error of the best found individual when compared with the known, or estimated, optimum value *opt_val*. It gives us a measure of how far are we from that *opt_val*.

Epop = (Abs(*opt_val*- pop mean fitness)/*opt_val*)100
It is the percentile error of the population mean fitness when compared with *opt_val*. It tells us how far the mean fitness is from that *opt_val*.

Gbest: Identifies the generation where the best value (retained by elitism) was found.

5. Results

The following tables show the results obtained under each method on the selected testing functions.

5.1. Griewangk's function

Method	3 parents	4 Parents	# Cross.
MP	0,09139	0,06516	1
MPIP	0,05178	0,03241	1
MCMP	0,03010	0,02904	2
	0,03009	0,02359	3
	0,01233	0,01477	4
	0,02480	0,01488	5
MCMP IP	0,00000	0,01005	2
	0,00739	0,00739	3
	0,04040	0,01773	4
	0,02719	0,00739	5

Table 1. Best values found under each method

Method	3 Parents	4 Parents	# Cross.
MP	5	10	1
MPIP	5	5	1
MCMP	50	60	2
	65	55	3
	70	65	4
	70	70	5
MCMP IP	80	80	2
	100	90	3
	95	90	4
	85	95	5

Table 2. Percentage of the population with Ebest under 0.1%.

Tables 1 and 2 show an increased improvement on performance from pure multiparent approach (MP) to the multiplicity-incest-prevention (MCMPIP) method. In this minimizing problem, best values found range from 0.09 to 0.0, specially when multiple crossovers are applied. And globally, the percentage of the population with Ebest values under 0.1% (that means a difference of 0.01 with the optimum value) also increases ranging from 5% to 100%.

Method	3 Parents	4 Parents	# Cross.
MP	0.19623	0.28100	1
MPIP	0.25447	0.28744	1
MCMP	0.11549	0.09671	2
	0.10694	0.12366	3
	0.07768	0.08540	4
	0.08111	0.07191	5
MCMP IP	0.06567	0.06122	2
	0.04576	0.06443	3
	0.04402	0.05710	4
	0.05636	0.05297	5

Table 3. Mean Ebest values found under each method

Method	3 Parents	4 Parents	# Cross.
MP	4.28554	5.13019	1
MPIP	4.80552	5.07019	1
MCMP	0.21196	0.11797	2
	0.12717	0.12382	3
	0.07768	0.08725	4
	0.08149	0.07191	5
MCMP IP	0.08685	0.08594	2
	0.04639	0.06508	3
	0.04654	0.05718	4
	0.05636	0.05297	5

Table 4. Mean Epop values found under each method.

In table 3, it can be seen that mean Ebest values are improved also when multiple crossovers are applied on multiple parents. When incest prevention is added enhancements are noticed for both numbers of parents used for experimentation.

All methods including multiple crossovers combined with multiple parents behave better than pure multiparent (MP). In particular when using incest prevention, MCMPIP show a substantial improvement, reducing Ebest up to a half of the corresponding value of MCPM which not uses incest prevention. In fact MCMPIP was the only approach that succeeded in finding the optimum many times, showing slight differences on Ebest values for any combination (n_1,n_2).
Nevertheless, at this point we cannot be conclusive about neither the optimal (n_1,n_2) combination nor about a clear effect of increasing n_2 for a constant n_1 on the quality of results.

When looking table 4, a noticeable effect can be observed when MCMP and MCMPIP are applied: All the *Epop* values are, when no identical, similar to the *Ebest* values.
This indicates a singular property of the methods using multiple crossovers; they tend to group the population around the best-valued individual, and this individual is always quite near optimal, or optimal.

The first two methods MP and MPIP, with single crossovers, show Epop values between 4 and 5% indicating a greater dispersion of individuals.

Method	3 Parents	4 Parents	# Cross.
MP	436.4	439.8	1
MPIP	371.9	377.2	1
MCMP	295.5	267.0	2
	278.6	235.6	3
	227.8	323.7	4
	200.0	251.4	5
MCMPIP	211.3	259.4	2
	258.1	181.2	3
	194.6	257.0	4
	121.8	155.8	5

Table 5. Mean Gbest values found under each method

In table 5 it can be observed that the generation where the best valued individual is found decreases, non monotonically, when the number of crossovers are augmented and this is more remarkable when incest prevention is also used.

5.2. Branin's Rcos function

This function resulted easier for diverse approaches of evolutionary computation and here it is not the exception. This fact can be appreciated in the mean Ebest values of table 6.

In all cases it can be observed an slight improvement when incest prevention is applied. Under MCMPIP a general tendency to enhance the quality of results is observed when the number of crossovers increases. Slighter best results are obtained under MCMPIP with 4 parents.

Method	3 Parents	4 Parents	# Cross.
MP	0.00226	0.00229	1
MPIP	0.00216	0.00215	1
MCMP	0.00232	0.00226	2
	0.00231	0.00229	3
	0.00228	0.00228	4
	0.00225	0.00228	5
MCMPIP	0.00218	0.00218	2
	0.00216	0.00216	3
	0.00216	0.00216	4
	0.00217	0.00215	5

Table 6. Mean Ebest values found under each method

Method	3 Parents	4 Parents	# Cross.
MP	0.11485	0.19760	1
MPIP	0.09687	0.13297	1
MCMP	0.00236	0.00228	2
	0.00231	0.00229	3
	0.00228	0.00228	4
	0.00225	0.00228	5
MCMPIP	0.00234	0.00235	2
	0.00216	0.00216	3
	0.00216	0.00216	4
	0.00217	0.00215	5

Table 7. Mean Epop values found under each method

Method	3 Parents	4 Parents	# Cross.
MP	444.2	431.8	1
MPIP	414.7	415.8	1
MCMP	186.5	201.2	2
	93.2	93.3	3
	109.2	135.1	4
	72.1	61.7	5
MCMPIP	182.2	194.1	2
	30.1	40.2	3
	28.9	25.0	4
	43.0	27.8	5

Table 8. Mean Gbest values found under each method

When observing mean Epop values, at table 7, again the population is grouped around the best-valued individual, and this individual is always quite near optimal, or optimal when multiple crossovers are applied. This effect is not detected under MP and MPIP.

In table 8, there is an indication that Gbest decreases as long as the number of crossovers augments and this effect is more strongly shown when MCMPIP is used.

6. Conclusions

In contrast with the single crossover per couple approach, Multiple crossover per couple (MCPC) permits more than one crossover operation for each mating pair exploiting features of previously found good solutions. The method showed its benefits and limitations, detailed in previous works.

To overcome these limitation a variant MCMPIP, including recombination of multiple parents and incest prevention is presented here.

Results indicate that this approach mitigates the possible loss of diversity generated by the application of multiple crossovers on a pair of parents and no extra adjustments, used before, seem to be necessary. Consequently the quality of results is at least as good as previous more complex approaches. Additionally, when observing the final population it was detected that all individuals are much more centred surrounding the optimum. This is an important issue when the application requires provision of multiple alternative near-optimal solutions confronting system dynamics as in most real world problems. Also speed of convergence, measured in number of generations, is augmented without increasing the risk of premature convergence.

Although we cannot be conclusive, it seems that by means of this approach the searching space is efficiently exploited by the multiple application of crossovers, efficiently explored by the greater number of samples provided by the multiple parents and premature convergence is avoided by incest prevention. For future work, as a first step, it remains to find optimal (n_1,n_2) combinations throughout of adaptive setting of parameters.

7. Acknowledgements

We acknowledge the cooperation of the project group for providing new ideas and constructive criticisms. Also to the Universidad Nacional de San Luis, the Universidad Nacional de La Pampa, and the ANPCYT from which we receive continuous support.

8. References

[Alfonso 98] Alfonso H., Cesan P., Fernandez N., Minetti G., Salto C., Velazco L., Gallard R. – *Improving Evolutionary Algorithms Performance by Extending Incest Prevention*- Proceedings del 4to Congreso Argentino de Ciencias de la Computación (CACiC'98), pp 323-334. Abstracts del Congreso, pp 69, Universidad Nacional del Comahue, Octubre 1998.

[Eiben 94] Eiben A.E., Raué P-E., and Ruttkay Zs., *Genetic algorithms with multi-parent recombination*. In Davidor, H.-P. Schwefel, and R. Männer, editors, Proceedings of the 3rd Conference on Parallel Problem Solving from Nature, number 866 in LNCS, pages 78-87. Springer-Verlag, 1994

[Eiben 95] Eiben A.E., van Kemenade C.H.M., and Kok J.N., *Orgy in the computer: Multi-parent reproduction in genetic algorithms*. In F. Moran, A. Moreno, J.J. Merelo, and P. Chacon, editors, Proceedings of the 3rd European Conference on Artificial Life, number 929 in LNAI, pages 934-945. Springer-Verlag, 1995.

[Eiben 97-1] Eiben A.E. and. Bäck Th., *An empirical investigation of multi-parent recombination operators in evolution strategies*. Evolutionary Computation, 5(3):347-365, 1997.

[Eiben 97-2] Eiben A.E. and van Kemenade C.H.M., *Diagonal crossover in genetic algorithms for numerical optimization.* Journal of Control and Cybernetics, 26(3):447-465, 1997.

[Eshelman 91] Eshelman L. J, Schaffer J.D. *Preventing Premature Convergence in Genetic Algorithms by Preventing Incest*, Proceedings of the Fourth International Conference on Genetic Algorithms, pp 115-122, Morgan Kauffman, San Mateo California, USA, 1991.

[Esquivel 97] Esquivel S., Leiva A., Gallard R., - *Multiple crossover per couple in genetic algorithms*. Proc. of the 4th IEEE International Conf. on Evolutionary Computation (ICEC'97), pp 103-106, Indianapolis, USA, April 1997.

[Esquivel 98] Esquivel S., Leiva A., Gallard R.: *Couple Fitness Based Selection with Multiple Crossover per Couple in Genetic Algorithms*. Proceedings of the International Symposium on Engineering of Intelligent Systems (EIS´98), La Laguna, Tenerife, Spain Vol. 1, pp 235-241, ed. E.Alpaydin. Publishesd by ICSC Academic Press, Canada/Switzerland, February 1998.

[Esquivel 99-1] Esquivel S., Leiva H.,.Gallard R., *Multiplicity in genetic algorithms to face multicriteria optimization,* accepted for publication and presentation in the 1999 Congress on Evolutionary Computation (IEEE). Washington DC.

[Esquivel 99-2] Esquivel S., Leiva H.,.Gallard R., *Multiple crossovers between multiple parents to improve search in evolutionary algorithms,* accepted for publication and presentation in the 1999 Congress on Evolutionary Computation (IEEE). Washington DC.

[Michalew. 96] Michalewicz, M., *Genetic Algorithms + Data Structures = Evolution Programs*. Springer, third revised edition, 1996.