IMPROVING EVOLUTIONARY ALGORITHMS PERFORMANCE BY EXTENDING INCEST PREVENTION

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ABSTRACT

Provision of population diversity is one of the main goals to avoid premature convergence in Evolutionary Algorithms (EAs). In this way the risk of being trapped in local optima is minimised. Eshelman and Shaffer [4] attempted to maintain population diversity by using diverse strategies focusing on mating, recombination and replacement. One of their approaches, called incest prevention, avoided mating of pairs showing similarities based on the parent's hamming distance.

Conventional selection mechanisms does not consider if the members of the new population have common ancestors and consequently due to a finite fixed population size, a loss of genetic diversity can frequently arise.
This paper shows an extended approach of incest prevention by maintaining information about ancestors within the chromosome and modifying the selection for reproduction in order to impede mating of individuals belonging to the same "family", for a predefined number of generations.
This novel approach was tested on a set of multimodal functions. Description of experiments and analyses of improved results are also shown.

KEYWORDS: Evolutionary algorithms, genetic diversity, premature convergence, selection mechanisms, incest prevention.

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1. INTRODUCTION

Natural systems provide a powerful source of inspiration for the design of artificial systems since even modest biological systems are adept at solving complex, real world problems.

Genetic Algorithms (GAs), a special class of Evolutionary Algorithms (EAs), attempt to use the mechanism of natural selection to search a problem space using the Darwinian theory of natural selection and population genetics [9]. They were developed by John Holland and coworkers [8] at the University of Michigan in the 1970s and have been studied by other research groups since. These studies have established the GA as a robust technique effective across a spectrum of problems even in the presence of difficulties such as noise, multimodality, high-dimensionality and discontinuity [3]. GA's have been applied to a wide variety of problems from pipeline engineering [6], VLSI circuit layout [1], [2], resource scheduling [12] and machine learning [7].

As shown in the following pseudo-code, a GA maintain a population of multiple individuals (*chromosomes*) which evolve throughout generations by reproduction of the fittest individuals. *Selection, crossover* and *mutation* are the main operators used for modifying individual features. So, it is expected that evolved generations provide better and better individuals (searchers in the problem space).

```
begin
  t:= 0;                                  // t is the generation number
  initialize  P(t);                       // P(t ) is the population at generation t
  evaluate individuals in  P(t);
  while end condition is not true do
  begin
    t := t + 1;
    select C(t) from P(t-1);              //C(t) stands for the mating pool
    recombine and mutate individuals in C(t) building C'(t);
    evaluate individuals in C'(t);
    select individuals from C'(t) to replace individuals in P(t-1) to build P(t)
  end
end
```

In the case of multimodal functions the problem space, also called the *fitness landscape*, provide 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.

A possible strategy to maintain population (genetic) diversity, attempting to avoid premature convergence is a mating strategy known as *incest prevention*.

This approach was first used by Eshelman and Schaffer [4] who avoided mating of those pairs showing similarities. As a bit string representation was used for their experiments similarities were determined on the parent's hamming distance.

The present work proposes an extended, representation-independent-approach of incest prevention. This goal is achieved by maintaining information about ancestors within the chromosome structure and modifying the selection for reproduction. In this way mating of individuals belonging to the same "family" is avoided for a predefined number of generations.

This novel approach was tested on a set of multimodal functions. We concentrate here on description of experiments and analyses of improved results on two of those functions.

2. 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 and to prevent it this approach allows recombination of individuals without common ancestors only.

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 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: to slow down the search process.

To make this point clearer we have to note 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 [9]. Focussing on this equilibrium problem significant research has been done [10], [5].

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).

```
procedure parent selection
  begin
    for 1 to sizepop
      select indiv-1 C(t)
      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);
  end for
  end
```

3. EXPERIMENTS DESCRIPTION

The experiments consisted in contrasting results obtained from EIP and a simple, but non canonical, genetic algorithm (SGA). Both approaches worked on the optimization of three testing functions *f1*, *f2* and *f3*, described below. For our experiments, series of 20 runs each with randomised initial population of size fixed to 80 individuals were performed on each function, using proportional selection, binary coded representation, elitism, one point crossover and bit flip mutation. The number of generations was variable and probabilities for crossover and mutation were fixed to 0.65 and 0.001 for *f1* and *f2* and 0.50 and 0.005 for *f3*, respectively. In order to isolate the convergence effect of EIP, the kind of selection mechanism, genetic operators and parameter settings chosen were those commonly used in optimising with a simple GA.

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

***f1*:** Michalewickz's multimodal function

$$f(x_1) = 2.0 + x_1 \cdot sin(10\pi \cdot x_1)$$
$$-1.0 \le x_1 \le 2.0$$
$$estimated \quad maximum \quad value : 3.850274$$

***f2*:** Michalewickz's highly multimodal function

$$f(x_1, x_2) = 21.5 + x_1 \cdot sin(4\pi \cdot x_1) + x_2 \cdot sin(20\pi \cdot x_2) \text{ , } for \text{ ;}$$
$$-3.0 \le x_1 \le 12.1, \quad 4.1 \le x_2 \le 5.8$$
$$estimated \quad maximum \quad value : 38.850292$$

***f3*:** Branins's Rcos Function

$$f_4(x_1, x_2) = \left(x_2 - \frac{5.1}{(4 \cdot \pi^2)} \cdot x_1^2 + \frac{5}{\pi} \cdot x_1 - 6 \right)^2 + 10 \cdot \left(1 - \frac{1}{(8 \cdot \pi)} \right) \cdot \cos(x_1) + 10,$$
$$x_1 = -5:10, \quad x_2 = 0:15;$$
$$minimum \text{ global value}: 0.397887$$

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

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

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

4. RESULTS

As a termination criterion, on each function a variable number of generation between a lower bound of 300 and an upper bound of 1000 was determined when the difference of population mean fitness, between two consecutive generations: $\varepsilon = \bar{f}_{P(t+1)} - \bar{f}_{P(t)}$ was less than 10^{-4}.

A general overview for EIP values contrasted with the corresponding SGA values, follows. Although the optimum was reached in many runs of each series, to contrast the performance of the algorithms only statistical data is reported. Mean values and corresponding variance for the above mentioned performance variables were studied. This was done for all functions and experiments.

Function *f1*

Ebest results were analysed for SGA and two EIP variants: EIP2G and EIP3G, which prevent incest during two or three consecutive generations respectively. In the following tables $\mu_{perfvar,}$

$\sigma_{perfvar}$, $\sigma/\mu_{perfvar}$ stands for the mean, standard deviation and coefficient of deviation of the corresponding performance variable (perfvar)

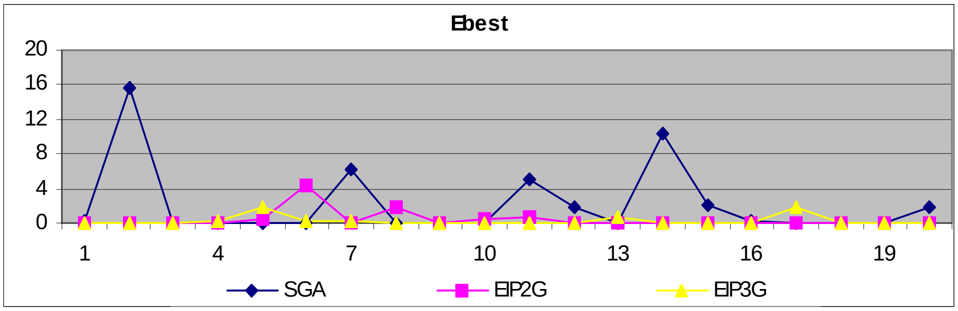

Fig. 1 Ebest values throughout the experiments for SGA, EIP2G and EIP3G on *f1*.

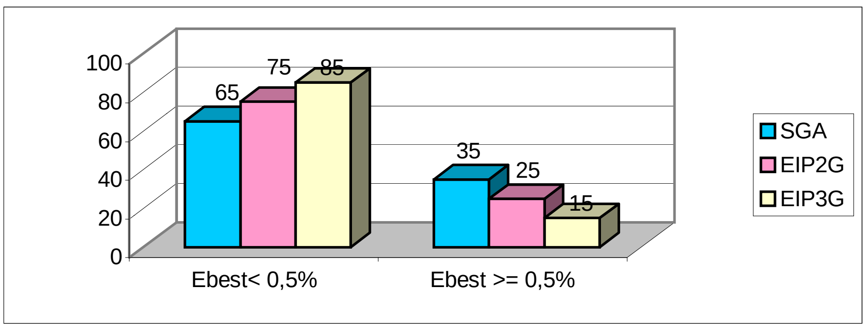

Fig. 2 Percentile of Ebest values below and above 0.5% throughout the experimentsfor SGA, EIP2G and EIP3G on *f1*.

	μ_{EBEST}	σ_{EBEST}	σ/μ_{EBEST}
SGA	2,17438421	4,1829588	1.923744
EIP2G	0,41339136	1,03931327	2.514111
EIP3G	0,24635909	0,57028618	2.314857

Table 1. Mean and standard deviation values for Ebest throughout the experiments for SGA, EIP2G and EIP3G on *f1*.

Figures 1 and 2, and table 1 show that the EIP approach clearly outperforms SGA on function *f1* optimisation: the number of optimal hits through the series is greater (fig. 1). It also can be perceived that, preventing incest during three consecutive generations is better than doing it on two generations only. Also it is important to remark that Ebest values are better and remain enough centralized around the mean in any EIP variant when they are contrasted against the SGA.

Analysis of Epop follows.

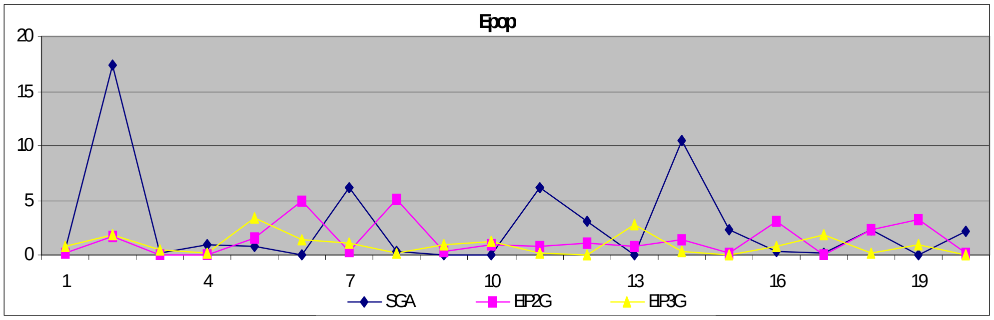

Fig. 3 Epop values throughout the experiments for SGA, EIP2G and EIP3G on *f1*.

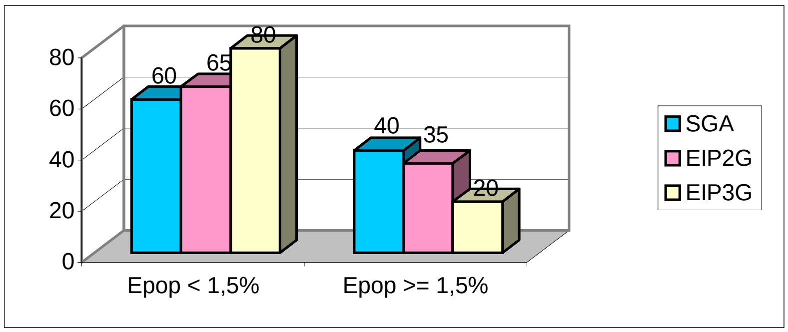

Fig. 4 Percentile of Epop values below and above 1.5% throughout the experimentsfor SGA, EIP2G and EIP3G on *f1*.

	μ_{EPOP}	σ_{EPOP}	σ/μ_{EPOP}
SGA	2,6557993	4,4210455	1.664676
EIP2G	1,3914906	2,0325115	1.460672
EIP3G	0,9162802	2,0163942	2.2006375

Table 2. Mean and standard deviation values for Epop throughout the experiments for SGA, EIP2G and EIP3G on *f1*.

Figures 3 and 4, and table 2 show that in the final stages, when the algorithm converges, population remains closer to the optimum value when either EIP approach is used. It also can be observed that, EIP3G is better than EIP2G. Epop values are also better and remain enough centralized around the mean in any EIP variant when they are contrasted against the SGA.

Function *f2*

Following figures and tables discuss on results for *f2*

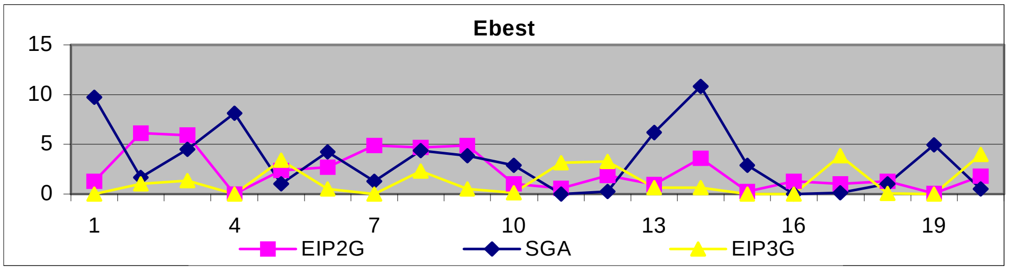

Fig. 5 Ebest values throughout the experiments for SGA, EIP2G and EIP3G on *f2*.

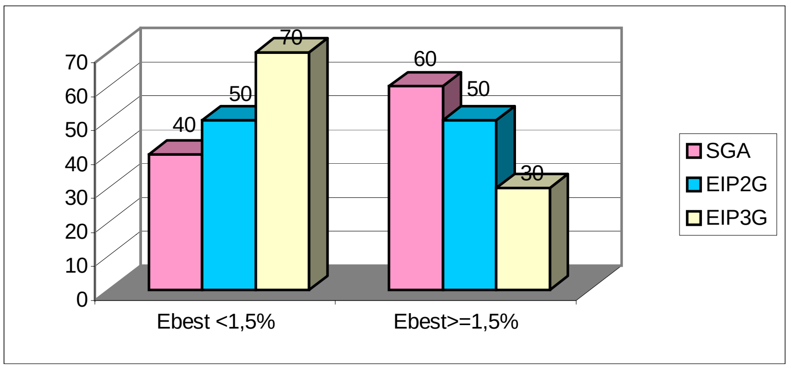

Fig. 6 Percentile of Ebest values below and above 1.5% throughout the experiments for SGA, EIP2G and EIP3G on *f2*.

	μ_{EBEST}	σ_{EBEST}	σ/μ_{EBEST}
SGA	3,43027374	3,25609318	0.949222
EIP2G	2,33285389	1,98179553	0.849515
EIP3G	1,247088019	1,482983636	1.189157

Table 3. Mean and standard deviation values for Ebest throughout the experiments for SGA, EIP2G and EIP3G on *f2*.

Although with less performance than in the *f1* case, for both approaches SGA and EIP, here again figures 5 and 6, and table 3 show that the EIP approach clearly outperforms SGA when optimizing function *f2*. The number of optimal hits through the series is greater (fig. 5). It also can be perceived that, preventing incest during three consecutive generations is better than doing it on two generations only. Here, also Ebest values are better and remain enough centralized around the mean in any EIP variant when they are contrasted against the SGA.

Analysis of Epop follows.

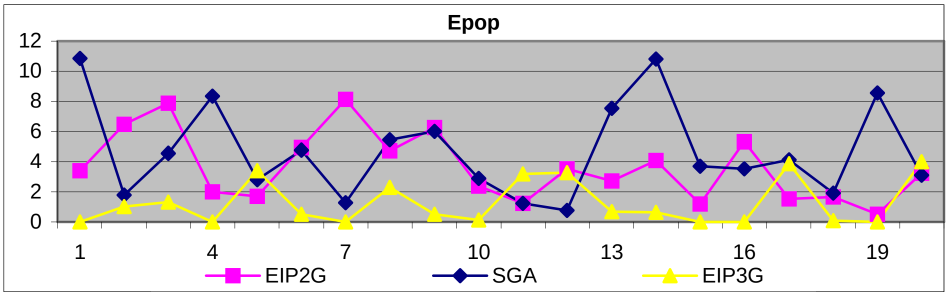

Fig. 7 Epop values throughout the experiments for SGA, EIP2G and EIP3G on *f2*.

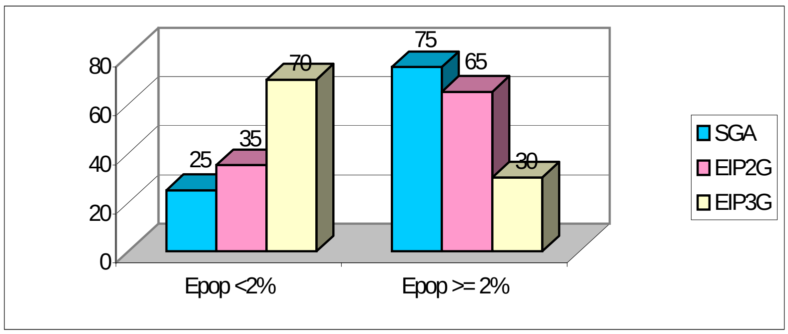

Fig. 8 Percentile of Epop values below and above 2% throughout the experimentsfor SGA, EIP2G and EIP3G on *f2*.

	μ_{EPOP}	σ_{EPOP}	σ/μ_{EPOP}
SGA	4,69946624	3,08721954	0.701725
EIP2G	3,64490413	2,27059911	0.622951
EIP3G	1,247088019	1,482983636	1.189157

Table 4. Mean and standard deviation values for Epop throughout the experiments for SGA, EIP2G and EIP3G on *f2*.

Figures 7 and 8, and table 4 show that in the final stages, when the algorithm converges, population remains closer to the optimum value when either EIP approach is used. It also can be observed that, EIP3G is better than EIP2G. Epop values are also better and remain enough centralized around the mean in any EIP variant when they are contrasted against the SGA.

Function *f3*

Following figures and tables discuss on results for *f3*

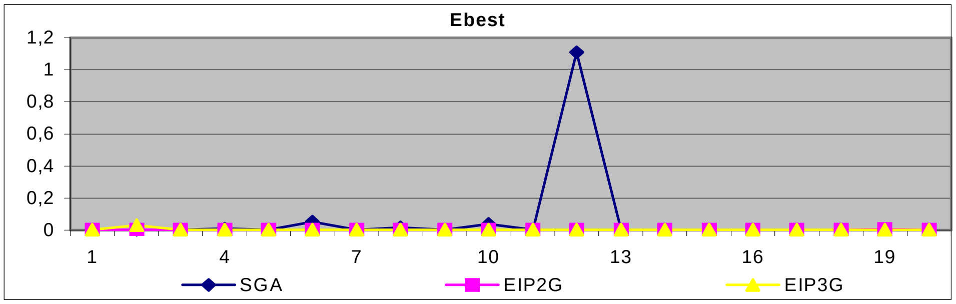

Fig. 9 Ebest values throughout the experiments for SGA, EIP2G and EIP3G on *f3*.

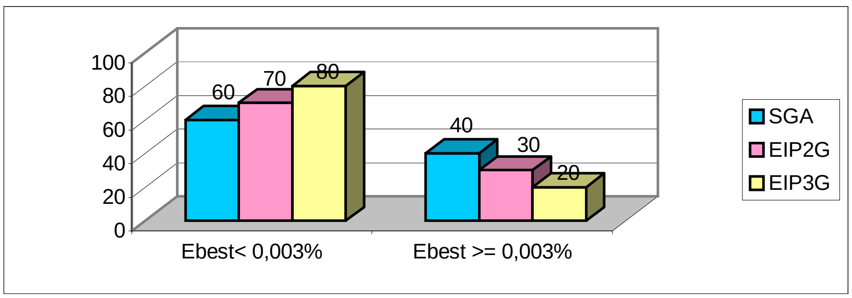

Fig. 10 Percentile of Ebest values below and above 0.003% throughout the experiments for SGA, EIP2G and EIP3G on *f3*.

	μ_{EBEST}	σ_{EBEST}	σ/μ_{EBEST}
SGA	0,06338075	0,24056168	3,79550068
EIP2G	0,00293075	0,06045548	20,6279894
EIP3G	0,00411278	0,05958231	14,4871133

Table 5. Mean and standard deviation values for Ebest throughout the experiments for SGA, EIP2G and EIP3G on *f3*.

Here with much better performance than when optimizing *f1* or *f2*, for any approach, figures 9 and 10 and table 5 show that the EIP approach clearly outperforms SGA when optimizing function *f3*. It also can be perceived that, preventing incest during three consecutive generations is better than doing it on two generations only. Here, again Ebest values are better but a slower dispersion around the mean in any EIP variant is observed.

Analysis of Epop follows.

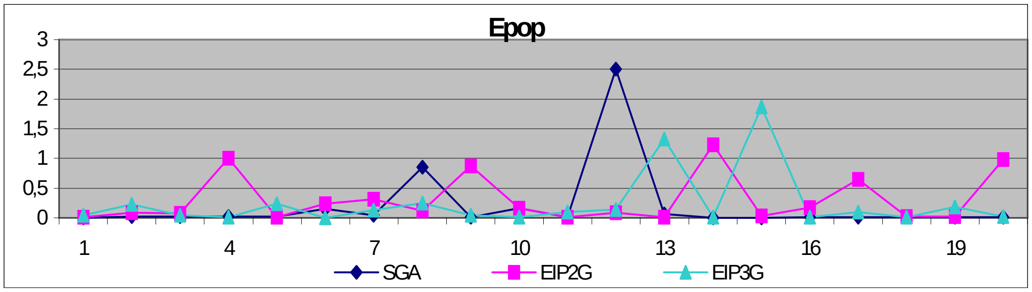

Fig. 11 Epop values throughout the experiments for SGA, EIP2G and EIP3G on *f3*.

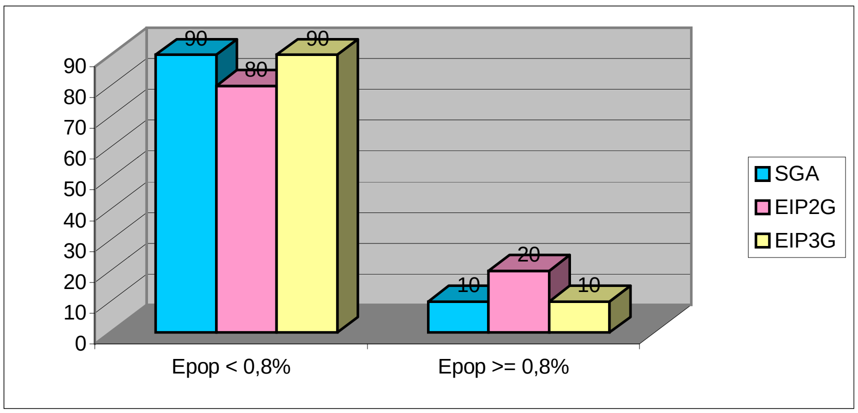

Fig. 12 Percentile of Epop values below and above 0.8% throughout the experimentsfor SGA, EIP2G and EIP3G on *f3*.

	μ_{EPOP}	σ_{EPOP}	σ/μ_{EPOP}
SGA	0,50199955	0,5002563	0,99652739
EIP2G	0,54270477	0,49906946	0,9195966
EIP3G	0,23704757	0,49792428	2,10052472

Table 6. Mean and standard deviation values for Epop throughout the experiments for SGA, EIP2G and EIP3G on *f3*.

In the case of function *f3*, although both approaches behave well figures 11 and 12, and table 6 show that in the final stages, when the algorithm converges, population remains closer to the optimum value when either EIP3G or SGA approach is used. It also can be observed that, EIP2G is less dispersed than EIP3G.

ANALYSIS OF GBEST

	SGA			***EIP2G***			***EIP3G***		
	μ_{GBEST}	σ_{GBEST}	σ/μ_{GBEST}	μ_{GBEST}	σ_{GBEST}	σ/μ_{GBEST}	μ_{GBEST}	σ_{GBEST}	σ/μ_{GBEST}
f1	207,15	83,53	0,40	182,9	72,04	0,39	182,9	72,04	0,39
f2	241,65	79,41	0,32	237,05	68,66	0,28	237,05	68,66	0,28
f3	565,9	262,60	0,46	379,45	224,70	0,59	379,45	224,70	0,59

Table 7. Mean, standard deviation and coefficient of deviation values for *Gbest* throughout the experiments on each function under each approach

Table 7, clearly shows that the best individual retained by elitism, is found in earlier generations when we use any EIP variant. Values are dispersed similarly around the mean for any approach.

5. CONCLUSIONS

EIP, a variant of incest prevention is presented here. Instead of using a measure of similarities between individuals through their Hamming distance to prevent recombination, EIP avoids breeding between individuals belonging to the same parentage for a limited number of generations.

This approach showed evidence of better performance when contrasted with traditional GA approaches on optimization of multimodal functions of varied difficulty. The optimal value was reached in many runs of each series and the mean value for the best individual throughout the series was always found earlier and was better than with SGA.

On the testing functions set, prevention through three consecutive generations showed better results than when it is applied through only two consecutive generations.

Experiments with a greater number of consecutive generations, not reported here, were also performed but the process shows higher overhead when looking for distinct ancestry of individuals in localized search. Further work would be necessary to determine an adequate limit to the number of consecutive generations involved in incest prevention.

This new variant presents also an alternative criterion to prevent incest that is independent of the individual's representation and consequently can be applied to integer, real, vectored or other representations without change.

Presently EIP is being tested on a wider set of testing functions and even if it can add some overhead due to the control, specifically when the genetic diversity of the initial population is not high, the results are promissory.

Further research will include thorough inspection of initial and evolved population diversity in order to maintain improved performance.

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7. REFERENCES

[1] Davis,L.(Ed). Genetic Algorithms and Simulated Annealing. London:Pitman. (1987),

[2] Davis,L., and Smith,D. Adaptive Design for Layout Synthesis. (Texas Instruments internal report). Dallas:Texas Instruments. (1985).

[3] De Jong, K A. Analysis of the Behavior of a Class of Genetic Adaptive Systems. Ph.D. dissertation. University of Michigan. (1975).

[4] 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.

[5] 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, University of La Laguna, España, Tenerife, Vol. 1, pp 235-241, ISBN 3-906454-12-6, Feb. 1998.

[6] Goldberg, D.E. Computer-aided Gas Pipeline Operation using Genetic Algorithms and Learning, Ph.D. thesis, University of Michigan. (1983).

[7] Goldberg, D.E. Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley, Reading, MA. (1989).

[8] Holland, J.H, Adaptation in Natural and Artificial Systems. Ann Arbor; The University of Michigan Press. . (1975).

[9] Holland, J.H. Genetic Algorithms and Adaptation. In O.G. Selfridge, E.L. Rissland, and M.A. Arbib (Eds.), Proc. Nato Adv. Res. Inst. on Adaptive Control of Ill-Defined Systems, 317-333. New York:Plenum Press. (1984).

[10] Michalewicz Z., Genetic Algorithms + Data Structures = Evolution Programs, Springer Verlag , Third, Extended Edition, 1996.

[11] Schaffer, J.D. (1987). Some effects of selection procedures on Hyperplane sampling by Genetics Algorithms and Simulated Annealing, 89-103. London:Pitman.

[12] Syswerda, G., and Palmucci, J. (1991). The Applications of Genetic Algorithms to Resource Scheduling. Proc. of the 4th International Conference on Genetics Algorithms, 502-508. Morgan Kaufmann, San Mateo, CA.