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Control of diversity in genetic algorithms using multimodal strategies

Control de diversidad en algoritmos genéticos utilizando estrategias multimodales

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Abstract: An optimization process is a kind of process that systematically comes up with solutions that are better than a previous solution used before. Optimization algorithms are used to find solutions which are optimal or near-optimal with respect to some goals, to evaluate design tradeoffs, to assess control systems, to find patterns in data, and to find the optimum values (local or global) of mathematical functions. A genetic algorithm is one of the optimization techniques. In this way, a heuristic search that is inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation which are population algorithms that emulate behavior similar to Darwinian natural selection. Taking into account these issues, this article shows the performance of a genetic algorithm designed, which

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allows to find several minimums within a function from the control of population diversity. To perform the tests, the algorithm with four different functions was used, with the particularity of having several minima with the same value. Proposed strategy was compared with a conventional genetic algorithm, the result was the conventional one can only find some of the minimums of the function and sometimes only one, while the proposal finds most of the minimums.

Keywords: Control of Diversity, Distances, Individual, Optimal Locals, Optimal Locations, Population.

Resumen: La búsqueda de la mejor solución posible a un problema se realiza con procesos de optimización, explorando los valores de los parámetros para los que cierta función objetivo tiene un valor óptimo (local o global). Entre las técnicas de optimización se encuentran los algoritmos genéticos, los cuales son de tipo poblacional o que emulan un comportamiento similar al de la selección natural Darwiniana. Este artículo muestra el desempeño de un algoritmo genético que permite encontrar varios mínimos dentro de una función a partir del control de diversidad de la población. Para realizar las pruebas se utilizó el algoritmo con cuatro diferentes funciones, con la particularidad de tener varios mínimos con el mismo valor. Se comparó esta estrategia propuesta con un algoritmo genético convencional, encontrándose que el convencional solo puede hallar algunos de los mínimos de la función —y en ocasiones solo uno— en tanto que la propuesta encuentra la mayoría de los mínimos.

Palabras clave: Control de Diversidad, Distancias, Individuo, Locales óptimos, Ubicaciones óptimas, Población.

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1. Introduction

The complexity of certain mathematical functions does not allow us to estimate an analytically solution to the problem, for this reason, strategies to find an approximate solution to the problem have been designed. One category of these strategies are the bio-inspired algorithms, among which are the genetic algorithms GA. GA is a metaheuristic search and optimization technique based on principles present in natural evolution. It belongs to a larger class of evolutionary algorithms. These algorithms have an advantage over others, since they allow the operation of multiple solutions emulating a behavior similar to that of the natural selection of the species. GA maintains a set of potential solutions for the problem. The idea is that "evolution" will find an optimal solution for the problem after a number of successive generations—similar to natural selection. A characteristic of this type of algorithm is that children inherit characteristics of their parents, however, no child is equal to them.

Following the rhythm of nature, to produce new individuals in the population these developed algorithms apply small genetic mutations. Groups of these populations are produced and new species are generated. With repetition of natural selection cycle among species, the one that best adapts to the environment survives or new species are created.

GA mimics three evolutionary processes: selection, gene crossover, and mutation. Similar to natural selection, the central concept of GA selection is fitness. The individuals that are more fit have a better chance for survival. Fitness is a function that measures the quality of the solution represented by the individual. Fitness function, or cost function, or object function provides a measure of the goodness of a given individual and therefore the goodness of an individual within a population. Since the fitness function acts on the parameters themselves, it is necessary to decode the genes composing a given chromosome to calculate the fitness function of a certain individual of the population. In essence, each individual within the population represents the input parameters. During the selection, individuals form pairs of parents for breeding. Each child takes characteristics from its parents. Basically, the child represents a recombination of characteristics from its parents: Some of the characteristics are taken from one parent and some from another. In addition to the recombination, some of the characteristics can mutate. Because fitter individuals produce more children, each subsequent generation will have better fitness. At some point, a generation will contain an individual that will represent a good enough solution for the problem.

Search strategies [1] based on the population represent a very appropriate tool to solve problems in the space of real or binary numbers. These algorithms explore the search space hoping to find optimal local or global, an example of them is the problem of the traveling agent for which only approximations have been found.

The population algorithms work on the most probable set of solutions called population, perform exploration and exploitation of the search space from the competition and cooperation between the solutions, some examples of these techniques are: the optimization based on swarms of particles [2], optimization based on ant colonies and genetic algorithms [3], [4].

Variations of algorithms mentioned above are concentrate on the grouping of possible solutions: approximation of multimodal functions [5], problems of niches [6], optimal at the borders [7] and also presents Variable Mesh Optimization (VMO), a population-based metaheuristic algorithm to explore the search space uses a population known as mesh. This mesh is expanded using different forms of solution generation. The advantage of using heuristic methods relies on their ability for estimating near optimal solutions, therefore ignoring analytic (often unknown) properties of the error function to be optimized.

In addition, the self-adapting algorithms are found as Hybrid Adaptive Evolutionary Algorithm (HAEA) [8]. This algorithm is a mixture of ideas borrowed from Evolutionary Strategies (ES), decentralized control adaptation, and central control adaptation. In HAEA a *niching* technique was implemented, combined with an evolutionary algorithm that adjusts the probabilities of the genetic operators while it evolves to arrive at a solution of the problem, this *niching* technique is based on deterministic crowding. Evolution using the niching technique with different genetic operators in real and binary coding schemes in some test functions was evaluated.

Niching is the segmenting the population of the GA into disjoint sets, intended so that you have at least one member in each region of the fitness function that is "interesting", this is for cover more than one local optima. Niching is a class of methods that try to converge to more than one solution during a single execution, they have the capacity to create and maintain several subpopulations within a certain search space. The proposal is to segment the population to be studied in disjoint sets or subpopulations, in each subpopulation there will be at least one member of the function that is "interesting"; thus, more than one local optimum is covered, since each of these disjoint sets corresponds to each optimum one is intended to find of a certain multimodal function.

In general, to apply the niching methods, you must take into account [9]:

- Initially, to assess the aptitude of individuals, the fitness value is obtained, it is always positive values. Then, the selected niching method is applied. Next, the selection operator is used, taking into account the implementation to be used.

- In order to establish the location of an individual in a subpopulation, a measure of dissimilarity should be used.

The sequential *niching* method [10], evolves in each iteration when it is implemented in a simple genetic algorithm. To avoid convergence in a single area of the search space several times, locate a solution and when it finds another niche ensures the population update with some individuals belonging to it. In the end, what the method does is to represent each niche for a single fitness to what is called Sharing or shared fitness.

With the *Sharing* method, the formation of different stable subpopulations is sought, bearing in mind that, theoretically, the number of individuals residing near an optimum is proportional to their value. In this way, many optima can be explored at the same time. To apply this method, each individual present in the population is degraded by a certain amount calculated based on the number of individuals similar that exist in the population.

The new "shared fitness" value (*shared*) $f'(i)$ of an individual i is given by (1) [9].

$$f'(i) = \frac{f(i)}{\sum_{j=1}^{n} sh(d_{ij})} \tag{1}$$

Where, $sh(d)$ is defined according to Ec (2)

$$sd(h) = \begin{cases} 1 - \left(\frac{d}{\sigma_{share}}\right)^{\alpha}, & si\ d < \sigma_{share} \\ 0, & en\ otro\ caso \end{cases} \tag{2}$$

The variables of the equation correspond to:

$f(i)$: Previous fitness value

sd : Sharing function

d_{ij} : Genotypic or phenotypic distance between individuals i and j

σ_{share} : Measure of dissimilarity

α : Constant (usually with value equal to 1)

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To solve numerical optimization problems, Herrera Lozada developed an artificial immune micro-system (called micro-SIA) based on the theory of clonal selection. He used the algorithm of the CLONALG artificial immune system, widely used in solving problems of optimization and pattern recognition. During the cloning phase, CLONALG drastically increases the size of its population, so this feature is attractive to propose a version with a reduced population of individuals. The author reduced the number of individuals in the population, in order to reduce the number of evaluations to the objective function, which was achieved by increasing the speed of convergence and decreasing the use of data memory [11].

It is worth mentioning the heuristic techniques with biological inspiration, which are usually known as bio-inspired algorithms [12], these are methods of optimization, search and learning, where their model is obtained from observations made of nature and applied to computer systems. These techniques are widely used, due to their high power of exploration, exploitation and parallelism generated by the creation of niches.

However, in this work, a conventional genetic algorithm with search space within the real to solve multimodal functions was used, this algorithm tries to keep several species within a population. The improvement of these mechanisms is one of the challenges of genetic programming, since, normally, evolutionary algorithms converge in a single optimal local or global. A conventional genetic algorithm was used because it is a very flexible and powerful search and improvement tool. The niching methodology was implemented for the maintenance of the species, using a strategy for the measurement of distances between individuals, by means of two guides who are in charge of traversing the function and providing information to the population of the most probable location of optimum local and global in order to observe the

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performance of the algorithm, four test functions were used [13], verifying that the algorithm finds all the local and global optima. The topic mentioned above and its relationship with this work are presented in this document, which is structured as follows: Section 2 establishes the materials and methods to show the functioning of the proposed algorithm. In section 3 the results obtained by testing the proposed technique with different mathematical functions are shown. In section 4 the conclusions constructed from the observations made during this investigation are presented.

2. Materials and methods

As a matter of fact, a conventional genetic algorithm for the implementation of the proposed algorithm was used, but it was adapted with two pointers whose function is to explore the search space, following the structure shown in Figure 1.

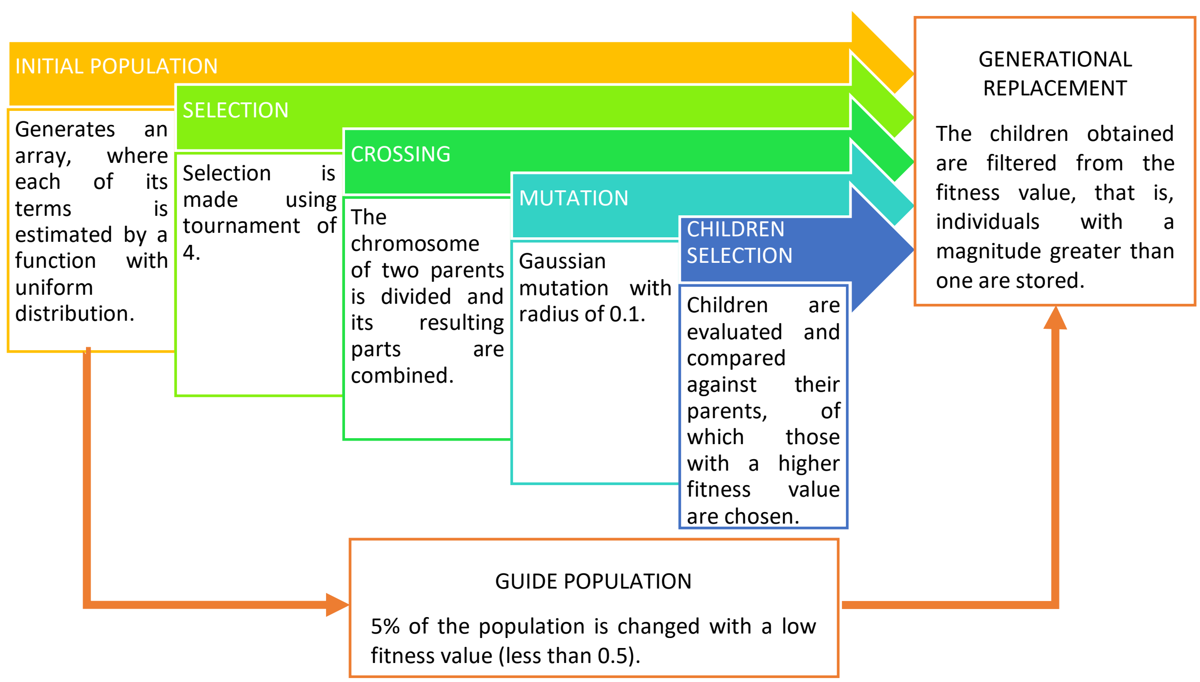

Figure 1. Nitching strategy used in research. Source: own.

This algorithm aims to ensure that the population is distributed evenly over each of the peaks of the test functions. The developed algorithm is shown in algorithm 1.

Algorithm 1. ***General algorithm***

```
Multimodal program ()
      Start variables;
      P0=Initial population U~[0,D];                  // D=Dimensions of the
      While != Stop condition                            search space.
            Parents=Tournament(P0);                   //Selection algorithm.
            If R~U[0, 1]<Pc                           //Pc=Recombination prob.
                  Children=Crossing(Parents)          //Lineal recombination.
            If R~U[0, 1]<Pm                           //Pm=Mutation probability.
                  Children=Mutation(Children)         //Gaussian Mutation.
            Points~U[0, the best];                    //Generate points.
            If pending(Points)<d                      //Points evaluation.
                  Guide=point;                        //Step distance.
            P0=Generational replacement (P0, guide); //Children selection.
            P0=Put new points (P0, Guide);            //Save new points.
      End while
End program
```

Algorithm 1. General algorithm of the developed application. Source: own.

3. Results

To verify the performance of the proposed algorithm, four test functions were used [1], all of them aim to reach a global minimum based on the approximation of these functions. Initially, a conventional genetic algorithm was used to evaluate them and then the proposed algorithm. The test functions are shown in equations (3), (4), (5) and (6).

$$f(x) = \sin^6(5\pi x) \tag{3}$$

$$f(x) = e^{-2*(\ln 2)*\left(\frac{x-0.1}{0.8}\right)^2} \sin^6(5\pi x) \tag{4}$$

$$f(x) = \sin^6(5\pi[x^{0.75} - 0.05]) \tag{5}$$

$$f(x) = e^{-2*(\ln 2)*\left(\frac{x-0.08}{0.854}\right)^2} \sin^6(5\pi[x^{0.75} - 0.05]) \tag{6}$$

The distribution of the initial population used in all functions is shown in Figure 2.

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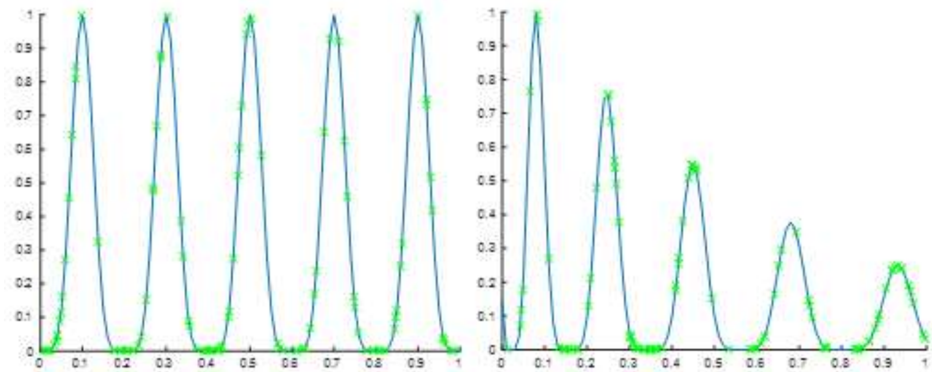
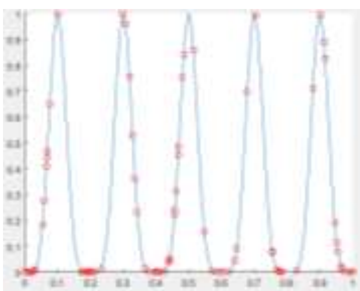
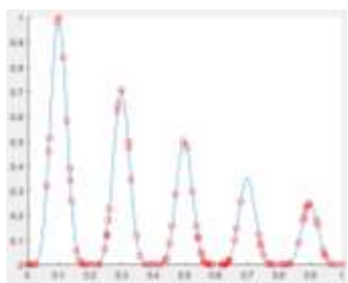


Figure 2. Initial population used to check the functioning of the algorithms. Source: own.

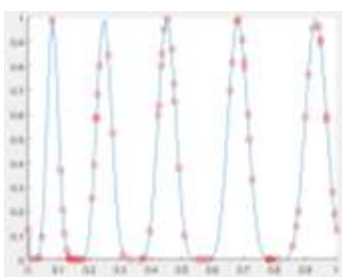
The graphic response obtained with the conventional genetic algorithm is shown in Figure 3. The numerical values of the response are found in Table 1.



A



B



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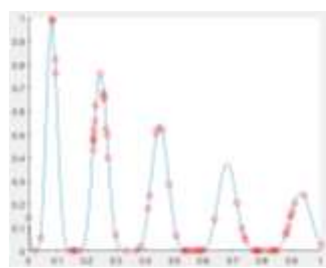

D

Figure 3. Response of the different functions using a conventional AGI genetic algorithm. A is the answer of (3). B response of (4). C response of (5). D response of (6). Source: own.

FUNCTION ( )	CRESTS FOUND	NICHE 1	NICHE 2	NICHE 3	NICHE 4	NICHE 5
1	4	1±0	1±0	0	1±0	1±0
2	4	0.99±0.01	0.7435±0.06	0.48±0.02	0	0.235±0.025
3	4	1±0.04	0	1±0.1	1±0.2	0.9471±0.2
4	4	0.97±0.03	0.75±0	0.475±0.025	0	0.222±0.088

Table 1. AGI Numerical Results. Source: own.

Making use of the modified genetic algorithm and the proposed algorithm, in the four functions and with the initial data of Figure 2, the graphs of Figure 4 were obtained as response. The numerical data of the results are in Table 2.

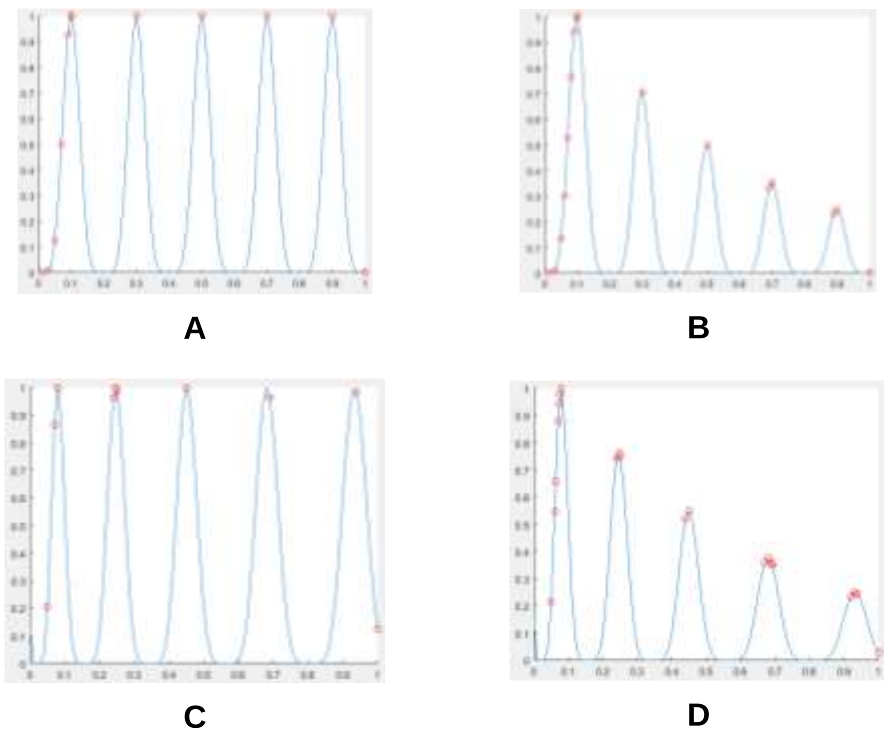

Figure 4. Response of the different functions using the modified genetic algorithm. A is the answer of (3). B response of (4). C response of (5). D response of (6). Source: own.

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FUNCTION ( )	CRESTS FOUND	NICHE 1	NICHE 2	NICHE 3	NICHE 4	NICHE 5
1	5	1±0	1±0	1±0	1±0	1±0
2	5	1±0	0.75±0	0.5±0	0.3536±0.04	0.25±0
3	5	0.998±0.02	0.998±0.02	0.9637±0.04	0.9471±0.06	0.9471±0.06
4	5	0.999±0.01	0.7518±0.05	0.5483±0.06	0.3580±0.002	0.2436±0.06

Table 2. Numerical results of the modified and proposed genetic algorithm. Source: own.

Performance comparison between two algorithms it is observed that modified algorithm the number of ridges increases with respect to the conventional genetic algorithm; the number of individuals located near the crests is greater in the modified algorithm, and it shows greater convergence towards the optimal ones to be located. 1000 evaluations of the fitness value were made with each algorithm, each of them was executed 20 times and its execution time was around 0.5 hours.

4. Conclusions

Performance of a modified genetic algorithm in four different functions, was analyzed in this document. The results indicate that the algorithm constitutes a promising proposal for this class of applications: in all the functions good solutions are found and the method behaves in a stable manner.

Therefore, the need to establish comparative criteria between a conventional genetic algorithm and the modified algorithm is imposed: although in the conventional genetic algorithm results are achieved similar to those obtained in the modified algorithm, the number of individuals must be taken into account that settled on the crests, for the case of the modified algorithm was

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greater than in the conventional algorithm, which shows that the performance of the proposal is better.

Tournament strategy as a selection mechanism was used, because roulette strategy let pass a lot of worse individuals, this caused the niches to be more dispersed.

The necessity to storage the points generated is a strategy that requires keeping individuals closest to a local minimum, this makes the algorithm converge quickly, but thanks to points guide the algorithm can continue to perform this exploration and when a new point is found possibly the mutation makes an exploitation that zone.

5. Future work

More refined genetic operators can be used for the function to adapt itself in the exploration and exploitation phases of the promising areas associated with local or global optima.

Likewise, incorporate a self-regulation function for the distance between the exploratory points, since the one that was used is fixed, which promises to improve the operation of the algorithm.

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