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## Research of niching genetic algorithms for optimization in electromagnetics

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### Abstract

Canonical genetic algorithms have the defects of pre-maturity and stagnation when applied in optimizing problems. In order to avoid the shortcomings, an adaptive niche hierarchy genetic algorithm (ANHGA) is proposed. The algorithm is based on the adaptive mutation operator and crossover operator that adjusts the crossover rate and frequency of mutation of each individual, and adopts the gradient of the individual to decide their mutation value. Traditional mathematical problems and an electromagnetic benchmark are solved using niching genetic algorithms to show their interest in real world optimization.

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*Keywords:* adaptive niche hierarchy genetic algorithm (ANHGA); hierarchy; mutation operator; crossover operator; gradient

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### 1. Introduction

Since Genetic Algorithms (GAs) was firstly put forward by J.H. Holland in 1970s [1], it has been widely used in optimizing complex functions, identifying parameters, optimizing neural networks and so on. GAs are stochastic optimization methods based on the mechanics of natural evolution and natural genetics [2,3]. They have been successfully applied to finding a global optimum of a single objective problem [4]. In the optimization of multimodal functions, however, the standard GA converges to only one peak since it cannot maintain controlled competition among the competing schemata corresponding to different peaks.

In recent years much work has been done with the aim of extending genetic algorithms to make it possible to find more than one local optimum of a function. The technique developed for this purpose is

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known as a niching method[5]. In natural ecosystems, a niche can be viewed as an organism's task, which permits species to survive in their environment. Species are defined as a collection of similar organisms with similar features. The subdivision of environment on the basis of an organism's role reduces interspecies competition for environmental resources. This reduction in competition helps stable subpopulations to form around different niches in the environment.

Section 2 introduces the niche genetic algorithms(NGA). Then combined niche with hierarchy technology are introduced in section 3. In section 4, the simulation result shows that application of the niching GAS on an electromagnetic benchmark is more efficient. Finally, we give some comments on in section 5.

## 2. Niche Genetic Algorithms

Niching methods have been developed to minimize the effect of genetic drift resulting from the selection operator in the traditional GA in order to allow the parallel investigation of many solutions in the population. In natural ecosystems, animals compete and survive in many ways and different species evolve to fill each role. A niche can be viewed as an organism task which permits species to survive in their environment. Species are defined as a collection of similar organisms with similar features. For each niche, the physical resources are finite and must be shared among the population of that niche.

The niche technology mainly adjusts the fitness of individuals and replacement strategy when generating the new generation. This makes the individuals evolve in special environment, ensures diversity of evolution population and gets many global optimums at the same time<sup>[6]</sup>. Representative niche methods are preselecting, crowding and sharing technology.

As the niche technology is an effective measure to maintain diversity when GAs are applied to optimize functions with many apices and tasks with many targets, it is mainly used to improve GA operators and doesn't change encoding structure. The research found the niche technology and hierarchy GA are mutual complementary in mechanism. The advantages of their combination will be better than those of single method. Then we propose adaptive niche hierarchy genetic algorithm(ANHGA). ANHGA changes in the following aspects: hierarchy structure is used in encoding method, niche technology is used in individuals operation and mutation probability is changed adaptively.

## 3. Adaptive niching hierarchy genetic algorithms

Using niche technology, ANHGA adopts speedup strategies during the process of encoding, selection and replacement to maintain reasonable population diversity and make GA not only converge but also discover many apices. ANHGA uses hierarchy structure to encode. Before selection, it adjusts individual fitness based on sharing strategy to increase select probability of small-scale species. During replacement, it selects individuals as the new generation individuals based on density and fitness<sup>[7,8]</sup>.

### 3.1. Hierarchy encoding structure

In hierarchy encoding method, each chromosome is composed of two parts: control gene and constitution gene. Control gene determines whether constitution genes are active. The active constitution genes are dominant and effective. The inactive constitution genes are recessive and ineffective. Chromosome includes dominant genes and recessive genes. The two kinds of genes are inherited to the next generation at the same time. The corresponding control genes determine whether they are transformed[9].

The control genes in hierarchy encoding are often binary encoding. The constitution genes are float encoding or binary encoding in allusion to practical problems. The number of constitution genes controlled by each control gene is variable with specific problems. The structure of hierarchy encoding is shown as figure1.

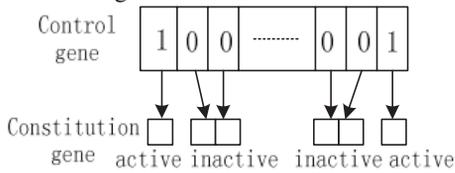


Figure 1. Structure of hierarchy encoding

In figure1, the upper-layer is control genes. The below-layer is constitution genes. In control genes, “1” expresses that the corresponding constitution genes are active and dominant. “0” expresses that the corresponding constitution genes are inactive and recessive. Decoding the dominant genes gets the solutions of the given problems. The recessive genes are inherited to the next generation with the dominant genes and may be activated during the process of evolution. The dominant genes may be transformed into dormancy. The effective gene segments are adjusted continually until getting the satisfied solutions.

### 3.2. Individual density

Similarity of individual gene codes embodies close degree among individuals. We define sharing function to express the density of individuals. So we introduce the concepts of sharing function and individual density.

Expression 1 let  $\vec{X}(t)$  be population of  $t$ th generation,  $X_i(t)$  be its constitution genes of  $i$ th individual,  $N$  be the size of population and  $d(i, j)$  be the distance between  $i$ th individual and  $j$ th individual. Then sharing function is defined as:

$$sh(d(i, j)) = \begin{cases} 1 - \left( \frac{d(i, j)}{\Delta(t)} \right)^\alpha & d(i, j) \leq \Delta(t) \\ 0 & else \end{cases} \quad (1)$$

where  $\Delta(t)$  is a variable which describes the close degree between  $i$ th and  $j$ th constitution genes. Its value is determined according to practical problems.  $\alpha$  is a parameter which controls the shape of sharing function. Usually  $\alpha$  is set to be 1.

It can be seen from equation 1 that when individuals are similar, the value of sharing function is big. Whereas when individuals are different, the value of sharing function is small.

Definition 2 set  $sh(d(i, j))$  as sharing function of  $i$ th individual and  $j$ th individual. The density of  $i$ th individual is defined as:

$$C_i(t) = \frac{1}{N} \sum_{j=1}^N sh(d(i, j)) \quad (2)$$

Obviously individual density can be used to appraise population diversity. The larger one is  $C_i(t)$ , the more is the number of individuals whose constitution genes are similar to those of  $i$  th individual. In such case, the population concentrates and loses diversity.

### 3.3. Fitness sharing<sup>[10,11]</sup>

In fact, individuals in certain range  $\Delta(t)$  can be regarded as a species. Big individual density means the number of this species is much. If some specie' density is too big, the fitness of all individuals in this species should be reduced and decreased their selected probabilities to maintain population diversity, create niche evolution environments and encourage small number species to multiply. As to population of  $t$  generation, the fitness of  $X_i(t)$  after sharing is defined as:

$$f_i'(t) = f_i(t) / C_i(t) \quad (3)$$

where  $f_i(t)$  is individual fitness of  $X_i(t)$  before sharing. GA carries out selection according to  $f_i'(t)$ . Supposing that the fitness of all individuals in  $i$  th species is  $f_i$ , the number of individuals in this species is  $N_i$ ,  $k$  is the number of species. Then the stable state of fitness sharing can be expressed as

$$f_i / N_i = f_j / N_j \quad (4)$$

where  $i \neq j$  and  $\sum_{i=1}^k N_i = N$

### 3.4. Adaptive mutation

when individual density  $C_i(t)$  is bigger, bigger probability should be applied to mutation operation. Considering the evolution time and individual density and ensuring algorithm to converge, the mutation probability is limited to (0,0.5). based on these, we suggest the following adaptive mutation probability.

$$P_m(t) = 1 - \frac{1}{1 + \exp(-t / C_i(t))} \quad (5)$$

### 3.5. Individual replacement based on crowding strategy

Set parent population be  $\vec{X}(t)$ , the population after mutation be  $\vec{X}'(t)$ . Mix population  $\vec{X}(t)$  and  $\vec{X}'(t)$ , adjust individual fitness according to the following formula:

$$fit_j'(t) = \beta \frac{f_j(t)}{\sum_{k=1}^N f_k(t)} + (1 - \beta) \frac{\frac{1}{C_j(t)}}{\sum_{k=1}^N \frac{1}{C_j(t)}} \quad j=1,2,\dots,2N \quad (6)$$

where  $\beta$  is a weight coefficient. The adjustment of fitness balances between individual fitness and density. Rank  $fit'_j(t)$  in descent order and select the first N individuals to compose the next generation. It is obvious that the individual replacement strategy based on crowding method can make uniform distribution and maintain population diversity preferably.

#### 4. Simulations

An function optimization problems are considered to compare and test the search ability of ANHGA, NGA and GA.

Shubert function:

$$\min f_2(x_1, x_2) = \left\{ \sum_{i=1}^5 i \times \cos[(i+1)x_1 + i] \right\} \times \left\{ \sum_{i=1}^5 i \times \cos[(i+1)x_2 + i] \right\} \quad -10 \leq x_1, x_2 \leq 10 \quad (8)$$

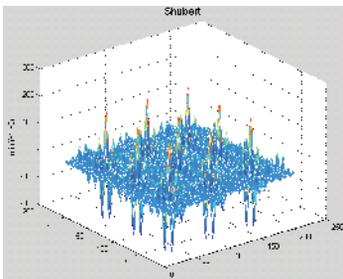


Fig. 1. Shubert function

Shubert function has 760 local optimal solutions. Among them, there are 18 optimums and the value is -186.7310 which can be seen from Fig.2. The objective function is converted to fitness value using the following formula:

$$F(x_1, x_2) = \begin{cases} 1 - 0.05 f_2(x_1, x_2), & \text{if } f_2(x_1, x_2) < 0 \\ 1, & \text{if } f_2(x_1, x_2) \geq 0 \end{cases} \quad (9)$$

During simulation, all three algorithms utilize the same control parameters listed in table 1. All three algorithms adopt proportional selection, single point crossover,  $P_c = 0.8$ . Three algorithms begin with the same initial population. Each algorithm began with the same initial population. Each algorithm is simulated 20 times for each optimized function. The simulation results are listed in table 1.

Table 1. Shubert function simulation results.

	SGA	NGA	ANHGA
Average numbers of global optimums	2.3	6.7	14.4
Average individual numbers of global optimums	3	19	36

It can be seen that the space search ability of GA is unsatisfactory. Its optimizing efficiency is inferior to NGA greatly. Shubert function is a complicated optimization problem. It is very difficult to find 18 global optimums at the same time. NGA can only find 6 or 7 optimums each simulation. However ANHGA can find dozens of optimums and sometimes 18 global optimums. Therefore hierarchy encoding can maintain population diversity effectively and ensure to not only converge but also find many apices.

Niching experiments were also carried out on an electromagnetic benchmark similar to that reported in [12]. The magnetizer geometry has been modified to depend on three parameters only. The pole shape consists of a circular arc centered at the point O of coordinates(0,x1) and joining the point P of coordinates(x2,x3)

Table 2 shows the range of the design variables used in this magnetizer problem. An additional constraint imposes a minimum distance of 55 mm between the point P and the point O to prevent the interception of the pole with the material to be magnetized.

Table 2. An example of a table

Design variable	Minimum value	Maximum value
$x_1$	-5.5mm	26mm
$x_2$	25.6mm	46mm
$x_3$	25.4mm	26.8mm

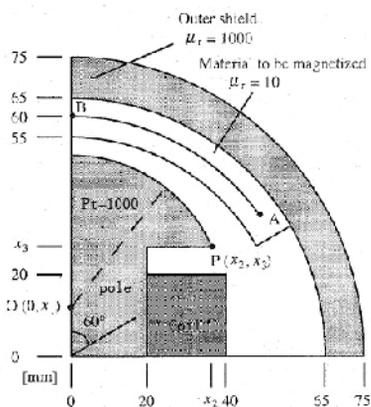


Fig.2 Geometry of the magnetizer

### 5. Conclusion

In this paper, niche technology and hierarchy genetic algorithm are combined and adaptive niche hierarchy GA based on sharing and crowding thought is put forward in this paper. This algorithm improves GA from not only encoding but also operators. These measures increase searching ability of the GA effectively, ensure population diversity and find many solutions of complicated problems. It is shown that the modified genetic algorithm is very effective to the multimodal optimization and appropriate for the design of multi-extremum complex system.

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