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Individual Aging in Genetic Algorithms

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Abstract: A concept of *age of individuals* for measuring their suitablity for participation in genetic operations for steady state GAs is introduced. Effective fitness of an individual depends both on its functional value and age. Age of a newly generated individual is taken as zero and every iteration it is increased by one. As in nature, *adult* individuals are considered more fit for genetic operations, compared to *young* and *old* ones. The model aims to emulate the natural genetic system in a more natural way. The effectiveness of this concept is demonstrated by solving complex function optimization problems. Resuts show that the scheme provides enhanced performance and maintains more diversity in the population thereby allowing the species to be robust to trace the changing environment.

Key words: Genetic algorithms, individual aging, bias

1. Introduction

Genetic Algorithms (GAs) [2] are executed iteratively on a set of coded individuals, called a *population,* with three basic operators: *selection/reproduction, crossover* and *mutation.* Each member of the population is called an individual and is represented by a chromosome. Usually, in generational replacement based GAs the whole population is replaced every iteration; on the contrary in steady state GAs (SSGA, say) only one or two individuals are replaced each generation. In this article we will be concerned with SSGAs only. Though several attempts are made to enhance the performance of the conventional SSGA [5,6], few methods [2] are suggested for *modeling them in a more natural manner* i.e., to emulate the natural genetic system more closely. The aim of this article is to introduce the concept of *aging of individuals* with iterations for measuring the suitability for their selection for genetic operations. Here the effective fitness of an individual at any iteration is measured by considering not only the objective functional value; but also including the effect of its *age.* We call this modified GA as **aGA**.

Experimental results on complex funtion

optimization problems show that the aGA gives enhanced performance and maintains more diversity in the population.

2. Aging of Individuals

In conventional genetic algorithms the suitablity of individuals for undergoing genetic operations is determined by their objective functional value only or sometimes picked up randomly. In natural genetic system, age of an individual also plays a key role to determine its suitability for mating. To emulate the natural genetic system more closely the concept of ***age of an individual*** may be introduced in GAs. As soon as a new individual is generated in a population its age is assumed to be zero. Every iteration age of each individual is increased by one. As in natural genetic system, ***young*** and ***old*** individuals are assumed to be less fit compared to ***adult*** individuals.

In SSGA once a particular individual becomes more fit, it goes on getting chances to produce offspring until the end of the algorithm (unlike nature), if a proportional payoff selection is used; thereby increasing the chance of generating similar type of offspring. More fit individuals do not normally die, and only the less fit ones die. In the present work, fitness of individuals with respect to ***age*** is asssumed to increase gradually upto a pre-defined upper age limit (number of itrations), and then gradually decreases. This, more or less, ensures a natural death for each individual keeping its offsprings only alive (like natural system). Thus, in this case a particular individual cannot dominate for a longer period of time. The concept may mathematically be modeled as follows.

In order to find out the suitability of an individual to be selected for genetic operations, two factors are taken into consideration. The first one is the objective functional value of the individual and the second is the ***age*** of it. Let fv_i be the functional value of an individual c_i and let its ***age*** be a_i. Then the effective fitness of this individual c_i may be defined as $fit_i = F(g(fv_i), h(a_i))$; where F, g & h are suitable functions. In the present study we have made F, g & h to lie in $[0, 1]$.

In the present work, since we are interested in maximizing some functions, we took g to be monotonically non-decreasing function defined as:

$$\begin{aligned} g(x) &= 2^{n-1}\left(\frac{x - x_{mn}}{x_{mx} - x_{mn}}\right)^n && \text{if } x \le \frac{x_{mn}+x_{mx}}{2} \\ &= 1 - 2^{n-1}\left(\frac{x_{mx} - x}{x_{mx} - x_{mn}}\right)^n && \textit{otherwise}; \end{aligned} \tag{1}$$

with $n \ge 1$; and x_{mn} & x_{mx} respectively are the minimum and maximum functional values attained in a particular iteration.

The function h can be chosen in a large number of ways. For this work we took

$$\begin{aligned} h(x) &= \frac{x}{b1} && \text{if} \quad 0 \le x \le b1, \\ &= 1.0 && \text{if} \quad b1 \le x \le b2, \\ &= 1.0 - \frac{x - b2}{b - b2} && \text{if} \quad b2 \le x < b, \\ &= 0.0 && \text{otherwise}; \end{aligned} \tag{2}$$

where b is the maximum age limit. In this case a number of individuals having ages in the range $[b1, b2]$ are assumed to be fittest (with respect to age) for genetic operations.

The function F can also be chosen in various ways. For the present study, we took F as

$$F(x_i, y_i) = (\beta x_i^\alpha + \overline{1 - \beta} y_i^\alpha)^{\frac{1}{\alpha}} \tag{3}$$

with $\beta\epsilon[0,1]$ and $\alpha > 0$. For our problem, $x_i = g(fv_i)$, & $y_i = h(a_i)$.

3. Experimental Results and Analysis

To demonstrate the effectiveness of the proposed concept a number of various types of complex functions are optimized. Here we present results of two different functions; $f6$ [1] and $f7$ [4]. Table 1 describes these functions.

Table 1: Functions used for optimization

$f6$	$0.5 - \frac{\{\sin(\sqrt{(x^2+y^2)})\}^2 - 0.5}{(1.0+0.001(x^2+y^2))^2}$
$f7$	$\{1+\sin(50(x^2+y^2)^{0.1})^2\}(x^2+y^2)^{0.25}$

In the present study the parameters for the GAs have been chosen as follows. A binary string (in which the sub-string length of each parameter was 22) was used for chromosomal representation. Population size was kept fixed at 40. Crossover and mutation probabilities were taken as 0.9 and 0.02, respectively. The worst two individuals were replaced by the two newly generated individuals in each iteration. 20000 iterations were performed in a simulation. 50 simulations were performed for each function with different values of β and $n = 2$ & $\alpha = 2$. Proportional payoff selection procedure was adopted. Maximum age limit (b) was fixed to 100.

Mean of the best solutions obtained by 50 simulations are put in Table 2. Note that in the table $\beta = 1$ corresponds to the conventional SSGA. From the table it is evident that the mean best solutions of the functions are better for most of the cases with the aGA compared to the SSGA. These show that the new algorithm (the aGA) gives more consistent and improved performance.

Table 2: Mean of best solutions ($n = 2$)

β value	$f6$	$f7$
1.0	0.876709	23.201474
0.9	0.872433	23.255219
0.8	0.900077	23.308927
0.7	0.895951	23.309240
0.6	0.908434	23.308242
0.5	0.910815	23.281775
0.4	0.921001	23.308521
0.3	0.914317	23.253741
0.2	0.894368	23.200840
0.1	0.898972	23.200482

It is expected that when β value is close to one there is no effect of aging; and thus the performance of aGA will be very close to that of SSGA. By decreasing the value of β, effect of aging is increased. When β goes very close to 0, the effect of functional value is mostly ignored for deciding the suitability of individuals, thus degrading the performance. Our emperical results, put in the table, also confirm this. From the results it is seen that a typical choice of β may be in the range [0.3-0.8].

3.1 Effect of aging on diversity

In SSGA if a particular individual has more functional value, it goes on getting chances to produce offspring thereby increasing the chance of generating similar type of offspring. Thus the population diversity reduces very fast. By introducing the concept of aging, no individual is allowed to dominate for a longer period of time; thus providing more scope of having various types of chromosomes in a pool.

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This, in turn, is expected to sustain the population diversity. To study the effect of *aging* on diversity we took the popularly used *bias* measure as in [3]. If a population has more bias, it is less diverse.

Let $s[i,j]$ represent the jth bit of the ith chromosome. Then the *bias* $b(t)$ of a population of size N with each chromosome having L bits for the tth iteration is defined as

$$b(t) = \frac{1}{2} + \frac{1}{N \times L} \sum_{j=1}^{L} \left(\left| \sum_{i=1}^{N} s[i,j] - \frac{N}{2} \right| \right). \tag{4}$$

Variation of the mean of bias values of 50 simulations with iterations are displayed in Fig. 1 (for the function $f7$ and a typical value of $\beta = 0.6$). The figure conforms to our earlier claim of sustaining more diversity by the aGA. Thus we can say that the aGA will have more scope to trace the change in the environment (non-stationary target) or will have more scope to come out from local optima.

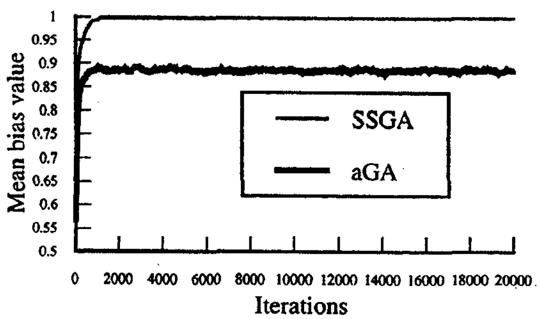

Fig. 1: Mean bias value with iterations for $f7$ ($\beta = 0.6$)

4. Conclusion

A concept of incorporating the effect of age of individuals (suitable for GAs having overlapping populations) for their selection for getting chances of genetic operations is introduced in the present article. Individuals which are at their *middle age* or *adult* are considered to be more fit compared to *younger* and *older* ones. Amount of weightage to be given on age of an individual to find out its suitability for genetic operations is also determined emperically. The effectiveness of this concept is demonstrated by solving complex function optimization problems. Results show that the aGA maintains more diversity in the population while giving enhanced performance.

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