Interactive Genetic Algorithm with Holding down Survival of the Fittest Based on Extinction Mechanism

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Abstract

Premature convergence and a user's fatigue are two problems in interactive genetic algorithm. An idea of extinguishing unsatisfactory patterns and preserving satisfactory patterns is proposed. A mechanism that preservation and extinction hold down each other is illustrated. Methods of extinguishing species based on taboo values and extinguishing individuals based on non-duplicate principles are expounded. Relationship between the algorithm's performance and its ten parameters is analyzed. Experimental results confirm feasibility and effectiveness of the proposed method.

Keyword: genetic algorithm, interaction, extinction mechanism, holding down rule.

I. Introduction

Interactive genetic algorithm (IGA) is simply a genetic algorithm (GA) in which individual's fitness is provided by user's subjective evaluation [1]. IGA has been successfully applied in fashion design, music composition, language processing, knowledge acquisition and data mining [2-5].

The first problem of GA is premature convergence. In order to avoid it, many methods are put forward. For example, Schraudolph et al proposed dynamic parameters encoding method [6]. Davis et al suggested that when a population converges to the same individual, execute mutation on most genes of the individual simultaneously [7]. De Jong presented many improved selection operators and fitness scale transformation strategies [8]. Whitley et al proposed Delta encoding [9] .Michalewicz considered a method to increase GA's local search ability [10]. Goldberg gave share-based niche technique [11]. However, none of them solves the problem that the algorithm spends too much time in searching subspace where the global optimum does not locate.

The second problem of GA is that the same individual repeats in the same or different generations. For IGA, not only a user's energy is wasted but also a pattern space is limited to be explored.

Aiming at solving the above two problems, an idea of extinguishing unsatisfactory patterns and preserving satisfactory patterns is proposed. A mechanism that preservation and extinction hold down each other is illustrated. Methods of extinguishing species based on taboo values and extinguishing individuals based on non-duplicate principles are expounded. Relationship between the algorithm's performance and its ten parameters is analyzed.

II. IGA with Holding down Survival of the Fittest Based on Extinction Mechanism

A. *Idea of Proposed Method*

The idea of the proposed method is that by using evolutionary historical information, the algorithm identifies satisfactory individuals and protecting them from being extinguished, identifies unsatisfactory individuals and extinguishes them. Because unsatisfactory individuals and species will never appear in offspring generation, one calls it extinction mechanism. How to identify unsatisfactory individuals and species is the problem to be solved. How to protect satisfactory individuals from being extinguished as well as to prevent satisfactory individuals from taking too much exploration time in offspring generation is also the problem to be solved.

To solve the above problems, one has to quote the definition of search division proposed in [12], in which the search space was divided into a taboo subspace S_{Ta}, a satisfactory subspace and an unknown subspace. No individual in taboo subspace is presented to a user for evaluation. Therefore, one can say that all the individuals presented to a user are from the satisfactory subspace or the unknown subspace. With a population evolves, more and more individuals will be identified as unsatisfactory and the search result will approach to the global optimum closer and closer.

Realization of the above division of search space is based on the definition of a gene unit [12] and its preference property. In [13], the following formula about relationship between the number of alleles of U_i and the number of individuals in a search space S is deduced as:

$$n(S) = \prod_{r=1}^{n} K^{m_r} \tag{1}$$

Definition 1: Let the *j*-th allele in U_i be $V_i^j (1 \le i \le n, 1 \le j \le K^{m_i})$, then call the point location in user's psychological space for the phenotype of V_i^j as its preference property, namely, $A(V_i^j)$,where

$$A(V_i^j) = \begin{cases} 2, \text{ a user is satisfied with } V_i^j \text{, then it is called as a satisfied value;} \\ 1, \text{ a user is not satisfied with } V_i^j \text{, then it is called as a taboo value;} \\ 0, \text{ a user's preference to } V_i^j \text{ is still unknown, then it is called as an unknown value.} \end{cases}$$

The realization of an extinction mechanism involves an encoding level and an individual level, whose realization will be explained in the next subsection.

B. Realizations of Extinction Mechanism and Holding down Method

From subsection II.A, one can conclude that all the species that contain taboo values should be extinguished because a user is unsatisfied with V_i^j. The holding down method is mainly realized by $A(V_i^j)$, which is described as follows:

(1) Individuals in offspring never come from a taboo subspace in which $A(V_i^j)=1$. Therefore, new individuals must come from a new subspace to meet the requirement of the population size. This is how a taboo value prevents satisfactory values from taking the whole population. Therefore, the diversity of a population is good.

(2) The order of updating $A(V_i^j)$ is that a satisfactory value is firstly determined and then a taboo value is determined. The principle of updating is as follows. 0 (an unknown value) can be replaced with 2(a satisfactory value) or 1(a taboo value), but 1 can't be permitted to replace 2. This kind of holding down mechanism can restrict an increase of the taboo subspace unlimitedly and avoid an optimum losing.

C. Mechanism of Decreasing Valid subspace by Taboo Value

In this subsection, a formula of the number of individuals in the taboo subspace and in the valid subspace with evolutionary generation is deduced. Let S_{Ta}^1 and S_V^1 be two sets of extinction species and valid species respectively. Let alleles $V_1, V_2, \cdots, V_w$ be taboo values, then:

$$S_{Ta}^1 = \bigcup_{i=1}^{w} S_{V_i} , S_v^1 = S - S_{Ta}^1 = S - \bigcup_{i=1}^{w} S_{V_t} \quad (2)$$

$$n(S_{Ta}^1) = \sum_{k=1}^{w} (-1)^{k-1} \sum_{1 \le i_1 < \cdots < i_k \le w} n(\bigcap_{j=1}^{k} S_{V_{i_k}}) \quad (3)$$

$$n(S_V^1) = n(S - S_{Ta}^1) = n(S) - \sum_{k=1}^{w} (-1)^{k-1} (\sum_{1 \le i_1 < \cdots < i_k \le w} n(\bigcap_{j=1}^{k} S_{V_{i_k}})) \quad (4)$$

Let $K(i,t)$ be the number of valid values of U_i that meet $A(V_i^j) \neq 1$. The formula for the number of individuals in the valid subspace and in the taboo subspace is as follows:

$$n(S_v^1(t_w)) = \prod_{r=1}^{n} K(r, t_w) \quad (5)$$

$$n(S_{Ta}^1(t_w)) = n(S - S_V^1(t_w)) = n(S) - n(S_V^1(t_w)) = \prod_{r=1}^{n} K(r,0) - \prod_{r=1}^{n} K(r, t_w) \quad (6)$$

The decrease rate of the number of individuals in the valid subspace caused by $V_{i(t_w)}^j$ is:

$$n(S_V^1(t_w)) / n(S_V^1(t_{w-1})) = K(w,t_w) / K(w,t_{w-1}) = (K(w,t_{w-1}) - 1) / K(w,t_{w-1})$$

From the above discussion, it can be seen that taboo values play an important role in species extinction to shrink the valid subspace. Therefore, it is important to decide which allele is a taboo value.

D. Determination of Taboo Value

In this subsection, one will quote the common operator and distinction operator proposed in [12]. Here let C_w be the common number of the most unsatisfactory individuals, and C_b be the common number of the most satisfactory individuals. It is obvious that the bigger the common number, the smaller the probability of determining $A(V_i^j)$ is [12]. Suppose the number of the accumulated most unsatisfactory individuals before generation *t* is Wind(*t*), and execute a common operator to all the Wind(*t*) individuals, then the times for executing the common operator is $C_{W_{ind}(t)}^{C_w}$.

The common operator plays two roles as follows. The first one is that it helps to get the set V_{sa} of satisfactory values V_i^j. The second one is that it helps to get the set V_{Ta} of taboo values V_i^j. Because the precondition of updating set V_{Ta} is $V_{Sa} \cap V_{Ta} = \varnothing$, it realizes the holding down mechanism. This is the first phase to decide a taboo value.

In the posterior phase of an evolution, the discrepancy between the optimal solution and the unsatisfactory individuals is small. Therefore, the effect of the common operator is restricted. There should be a substitute method to keep an increase rate of the taboo subspace. The character of the unsatisfactory individuals is certainly different from that of the fittest. Therefore, one introduces a distinction operator to get a taboo value. When the Hamming distance between the most unsatisfactory individual and the fittest individual is less than a set threshold Δ_d, it is time to execute the distinction operator. This is the second phase to determine a taboo value.

Based on a taboo value, the extinction species can be determined and the taboo subspace can be updated. Then a new division of the search space will help to realize the holding down mechanism.

E. Determination of Extinction Individuals

The most obvious character of IGA is that compared with a tireless computer, a user is apt to be tired, which limits the population size and the number of generations.

Besides the method of extinguishing species mentioned before, a method of extinguishing an individual is also presented. One calls it as "two none-duplication methods" for short.

Suppose the population size is n_p. In each generation, all individuals except the one with the highest fitness are the non-optimum individuals. Let the number of the non-optimum individuals in generation *t* is $n_1(t)$. Let the probability of extinguishing the non-optimum individuals be $c(0 \le c \le 1)$, the algorithm can prevent the non-optimum individuals from presenting to a user according to the above probability. This is the first non-duplicate method.

Another non-duplicate method is also adopted. It is also prevented that presents the same individual in the same generation to a user, which will save a user's energy and maintain the diversity of a population. This is the second non-duplicate method.

Hence, before the offspring being presented to a user, they are checked at least three times. The first time is to check whether there is identical individual in the same generation or not. The second time is to check whether all the individuals are from the valid subspace or not. The third time is to check whether the population size is equal to a set value. If the number of offspring is less than the population size, the algorithm will select individuals with the smallest Hamming distance and the highest fitness from the valid subspace.

The relationship between the number of individuals determined by the above non-duplicate methods in the taboos subspace S_{Ta}^2 and a generation *t* is:

$$n(S_{Ta}^2(t)) = \sum_{i=1}^{t}(c \cdot n_1(i)) = c \cdot \sum_{i=1}^{t} n_1(i) \tag{7}$$

The aim of the proposed method is to get high performance. The algorithm's performance will be analyzed from the point of a decrease rate of the valid subspace and the maximum evolution generation.

F. Algorithm's Performance Analysis

The decrease of the valid subspace will lead the algorithm to spend more time on exploring the subspace where the global optimum locates. Therefore, a decrease rate of the valid subspace can be taken as an indication of the algorithm's performance.

From II.C and II.E, an expression of the taboo subspace is $S_{Ta} = S_{Ta}^1 \cup S_{Ta}^2$. And the number of individuals in the taboo subspace is:

$$n(S_{Ta}(t)) = \prod_{r=1}^{n} K(r,0) - \prod_{r=1}^{n} K(r,t_w) + c\sum_{i=1}^{t} n_1(i) - n(\bigcap_{i=1}^{2} S_{Ta}^i(t)) \tag{8}$$

The number of individuals in the valid subspace is:

$$n(S_V(t)) = n(S) - n(S_{Ta}(t)) = \prod_{r=1}^{n} K(r,t) + n(\bigcap_{i=1}^{2} S_{Ta}^i(t)) - c \cdot \sum_{i=1}^{t} n_1(i) \tag{9}$$

The common-accumulation effect leads $K(r,t)$ to decrease rapidly, and the valid subspace decreases in product form. The second extinct method shown in formula (9) indicates that $c \cdot \sum_{i=1}^{t} n_1(i)$ will also contribute to decrease of the valid subspace. Therefore, a decrease rate of the valid subspace is much fast.

Next, the maximum evolution generation T is analyzed. Only the case determined by taboo values is considered.

When the algorithm converges to the global optimum, the number of taboo values is:

$$n_{Ta=1}(T) = \sum_{i=1}^{n}(K(i,0) - 1) = \sum_{i=1}^{n}(K(i,0)) - n \tag{10}$$

Let the average number of taboo values gained by $\sum_{i=1}^{C_w - 1} C_{W\_N_{ind}(t)}^{i} \cdot C_{W\_O_{ind}(t)}^{C_w - i} + C_{W\_N_{ind}(t)}^{C_w}$ common operators be μ. Then the maximum evolution generation T satisfies $\mu \cdot T \le n_{Ta=1}$. One can get:

$$T = \lceil n_{Ta} / \mu \rceil \qquad (11)$$

Formula (11) is based on the condition that there is only one individual left in the valid subspace. In fact, as a method of optimization, IGA can get the global optimum earlier than T obtained by formula (11) which will be verified by an experiment in IV.

III. Comparison with Traditional IGA

The proposed method is compared with a traditional IGA mainly in the view of the search space.

Firstly, the extinction mechanism continually decreases the valid subspace with a population evolving, while the valid subspace does not decrease in a traditional IGA.

Secondly, exploring a new subspace by genetic operators is limited in the valid subspace for its decrease with a population evolving. Therefore, the performance of the proposed method depends less on genetic operators than that of a traditional IGA.

Thirdly, the proposed method has ability to explore a new subspace. Information on taboo is accumulated during each generation and it directs the search to effectively explore a new subspace. The proposed method tries to assign an experiment to every point randomly out of the taboo subspace, while a traditional IGA is apt to explore some sub-optimum subspace.

Fourthly, the proposed method approaches to the global optimum in two ways, namely, preserving superior individuals and extinguishing inferior individuals. A traditional IGA only preserves possible super individuals, while the proposed method not only preserves the optima but also reduces the valid subspace by extinction mechanism.

IV. Experiment and Analysis

In this section, an experiment and its analysis are given.

The object for this experiment is fashion design. The aim of fashion design is to get good design. However, different users have different opinions on good design. Therefore, it is impossible to establish a general explicit function for fashion design. An IGA- based fashion design system is explained in [12].

The proposed method speeds up an evolution, alleviates a user's fatigue and avoids premature convergence mainly by two methods. The first one is to reduce the size of a valid subspace by taboo values and the second one is to preserve the optima by satisfactory values. Therefore, the performance of the proposed method can be evaluated according to the number of taboo values and that of satisfactory values during an evolution.

The size of a taboo subspace relates to the number of taboo values and non-duplicate rules. Just as a satisfactory subspace, the parameters related to the size of a taboo subspace include $OP_c^w, C_w, OP_s^w, P_c, P_m$ and c. P_c is used to extinguish individuals and P_m is used to extinguish species.

Non-duplicate rules are related to c, and the bigger the c, the more individuals are extinguished.

Besides the above parameters, the number of global optima is also a factor that effects the performance of the proposed method. The more the global optima, the more survival of the fittest holds down extinction. The slower an increase rate of the number of taboo values, the more the convergence generation needs.

In GA, fitness is the most important factor for a population evolving. Therefore, it is prone to premature convergence in IGA if a user is not careful of assigning fitness. During the experiment, most users are familiar with the proposed method. There are mainly three methods to assign fitness. The character of the first method (#1) is that a user assigns zero to all the individuals that include none of the satisfactory values, and in the second method (#2), a user assigns fitness 1000 to all the individuals that include some satisfactory values and assigns fitness 500 to other individuals. The character of the third method (#3) is that a user assigns fitness according to a psychological space of individuals. For the three different methods, convergence generation T and the number of taboo values are different. The fastest method to converge is #1 that has the largest number of taboo values, while the slowest is #3 that has the smallest number of taboo values.

There is a phenomenon of losing the global optimum. But most cases are caused by being unfamiliar with the proposed method.

The aim of this experiment is to test the performance of the proposed method. The performance mainly includes T, $\Delta n(S_{Ta})$. The performance is mainly effected by the above ten parameters. Therefore, it is significant to check the parameters' effect on the method.

The following data are sampled from #1. The result is recorded when all the parameters are set to be default, namely, OP_s^w =1, OP_s^b =1, OP_c^b =1, OP_s^w =1, P_c =0.5, P_m =0.005, C_b =2, C_w =2, c=0.5, O_{pn} =1. Then, the result is also recorded when other parameters are set to be default and only one parameter is changed, and their differences in $\overline{T}$ and $\overline{\Delta n(S_{Ta})}$ are compared. All the results are calculated statistically with the sample size 20 [14].

The averages of $\overline{T}$ and $\overline{\Delta n(S_{Ta})}$ in the above cases are shown in Table 1. The column OP_s^w =1 is the result when all the parameters are set to be default, and other columns are results when other parameters are set to be default and only one parameter is changed.

Table 1. Averages of convergence generation $\overline{T}$ and increase rate $\overline{\Delta n(S_{Ta})}$ of taboo subspace

	OP_s^w		OP_s^b	OP_c^b	OP_c^w	P_c	P_m	C_b	C_w	c	O_{pn}
	0	1	0	0	0	0.99	0.99	4	4	1	2
$\overline{T}$	14.8	7.5	7.9	9.1	12	7.9	8.4	6.1	9.7	8	14.4
$\overline{\Delta n(S_{Ta})}$	171.5	453.8	447.0	449.4	246.4	484.6	480.4	576.1	320.0	460.5	274.9

Contribution rates of the three main parameters are shown in Table 2.The accumulated contribution of the three parameters is approximate 0.60, so they effect on the performance of the proposed method significantly.

Table 2. Contribution rates of three main parameters

$OP_s^w=0$	$O_{pn}=2$	$OP_c^w=0$	sum
0.225	0.214	0.152	0.591

The correlation coefficients between the performance of the algorithm and ten parameters are shown in Table 3.

Table 3. Correlation coefficients ρ between parameters and T, $\Delta n(S_{Ta})$

	OP_s^w	OP_s^b	OP_c^b	OP_c^w	P_c	P_m	C_b	C_w	c	O_{pn}
T	-0.561	-0.020	-0.267	-0.462	0.025	0.134	-0.382	0.309	0.035	0.767
$\Delta n(S_{Ta})$	0.816	-0.156	0.668	0.0184	0.131	0.107	0.445	-0.816	0.028	-0.651

In order to verify the efficiency of the proposed method, a comparison experiment is done. Other methods are an autonomous IGA [15], a hierarchy IGA [16] and an adaptive hierarchy IGA [17] . The genetic parameters of the proposed method are default and those of other genetic algorithms are the same as the proposed method. All of the methods adopt survival of the fittest to ensure their convergence. The stop condition for all the algorithms is that a user stops manually. It can be seen from Table 4 that the proposed method has the highest performance.

Table 4. Comparison result

	proposed method	hierarchy IGA	adaptive hierarchy IGA	autonomous IGA
$\overline{T}$	7.5	14.6	16.4	24.2

V. Conclusion

In this paper, an extinction mechanism and a holding down method are proposed. Its aim is to make it spend less time in searching a subspace where the global optimum does not locate. The realization of species extinction and individual extinction is given. Relationship between the performance of the proposed method and ten parameters is presented. Finally its efficiency is validated by a comparison experiment.

There are still some issues to be discussed further. (1)The proposed method will spend more time in exploring a subspace where the global optimum does not locate. Therefore, if a search space is very big, then the extinction mechanism will be waste of exploration. (2) a user's preference is apt to be floated in an evolution [18]. Therefore, a precondition for the reliability of the common and distinction operators is that a user's preference does not float again.(3)The sensitivity analysis of the parameters proposed in this paper.

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