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Full Length Research Paper

Fuzzy sexual selection and multi-crossover for genetic algorithm

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This paper introduces a new selection scheme inspired by sexual selection and some new methods based on combination of crossovers, concept of sexual selection and lifetime for chromosomes. A bi-linear allocation lifetime approach is used to label the chromosomes based on their fitness value. After selecting a label for each chromosome, using fuzzy rules and selecting a suitable crossover method, initially prepared for recombination in the genetic algorithm (GA). Computational experiments are conducted to compare the performance of this new technique with some commonly used crossover mechanisms found in a standard GA in order to solving some numerical functions from the literature.

Key words: Genetic algorithm, selection, sexual selection, fuzzy, crossover.

INTRODUCTION

Genetic algorithm; is a family of computational models inspired by natural evolution that was originally proposed by Charles Darwin (Darwin, 1859). There are three stages in the utilization of GA: encoding, selection and recombination. In this paper the study uses binary encoding for the proposed GA. After deciding on an encoding, the second decision in making use of the GA is how to perform the selection, that is, how to choose the chromosomes in the population that will create offspring for the next generation and how many offspring each will create. In this paper; the study introduces a new selection scheme inspired by sexual selection. The third decision to make in implementing a GA is the recombination. Here, the study introduces some methods in crossover based on combine crossovers on binary encoding.

Premature convergence is a classical problem in finding optimal solution in Genetic Algorithms (GAs). The population diversity is the possible way of avoiding the premature convergence in a GA. If the diversity of population is low, the GA will converge very quickly. On the other hand, if the diversity of population is too high, the GA will takes a lot of time to converge and this may caused wastage in computational resources. In order to recognize and to avoid premature convergence some researchers use population diversity. In this study, the authors look at two categories: diversity measures (Glickman and Sycara, 2000; Morrison and De Jong, 2001) and maintenance of diversity (McPhee and Hopper, 1999; Reinhard and Bernard, 1992). Some researchers try to control the diversity of population (Herrera and Lozano, 1996). The sexual selection scheme was inspired by the idea of sexual selection proposed by Darwin which refers that the mating choices in some species are determined by the female. Fisher (Fisher and Bennett, 1999) was the first to provide a probable solution to the problem of selection for mal-adaptive traits. Kirkpatrick, 1987; Kirkpatrick and Ryan, 1991) developed a simple systematic model of sexual selection by working on mates with exaggerated secondary sexual characteristics that actually reduce the ability of the individual behaviour for them to survive. Some forms of crossover operators are more suitable to tackle certain problems than others, even at the different stages of the genetic process in the same problem. For this reason, techniques that combine multiple crossovers, called hybrid crossover operators, have been suggested as alternative schemes to the common practice of

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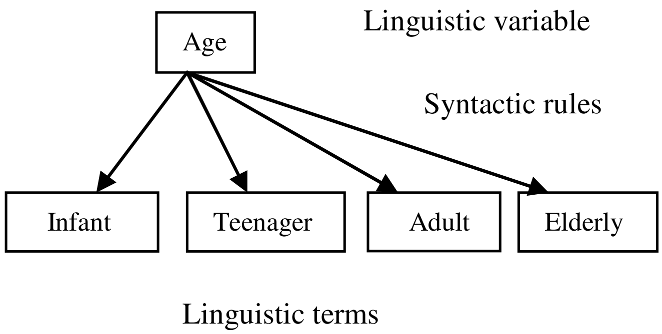

Figure 1. The linguistic variable "age".

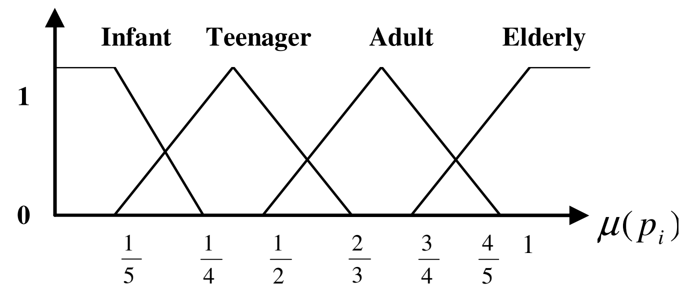

Figure 2. The age linguistic variable.

applying only one crossover model to all the elements in the population (Arabas et al., 1994; Herrera et al., 2003).

In this study, the authors use the labels that were taken from the lifetime approach for sexual selection and the fuzzy linguistic rules for selecting suitable crossover to control the diversity of the population. For recombination in this paper, they introduce some new methods that use binary encoding. These methods are based on the combination of k-point crossover, uniform crossover, and random numbers. In this technique, each generation diversity of population is found to be high. Chromosomes with high fitness may so elitism selection was used for improvement.

Fuzzy rules systems

A rule system consisting of a number of rules with a condition part and an action part: IF "condition", THEN "action". The condition part is also known as the rule premise, or simply the IF part. The action part is also called the consequence or the THEN part. A fuzzy rule system is a rule system whose variables or part of its variables are linguistic variables. A linguistic variable is characterized by a quintuple (Glickman and Sycara, 2000 M,U) in which x is the name of the variable, T(x) is the term set of x, that is, a set of linguistic values of x, which are fuzzy sets on the universe (U), G is the syntactic rule for generating the names of values of x and M is a semantic rule for associating each value with its meaning, that is, the membership function that defines the fuzzy set (Jin, 2003). In this paper they also use a linguistic variable, age, for chromosomes. Figure 1 shows a linguistic variable age: Infant, Teenager, Adult and Elderly are the linguistic values. The membership func-tions for the linguistic terms are called semantic rules.

Fuzzification interface

In this study, to find a membership function, the authors use fitness function of each chromosome and average of fitness functions in each generation. Each chromosome has its own label determined by membership function.

Let $\varphi = \dfrac{f_i - f_{\min}}{f_{avr} - f_{\min}}$, $\phi = \dfrac{f_i - f_{avr}}{f_{\max} - f_{avr}}$ and $\tau = f_{avr} - f_i$

then membership function is:

$$\mu(c_i) = \begin{cases} \dfrac{L + \alpha\varphi}{n} & \tau \geq 0 \\ \dfrac{\beta + \alpha\phi}{n} & \tau < 0 \end{cases} \qquad (1)$$

Where c_i = chromosome i, L = minimum age, U = maximum age, f_i = fitness value of chromosome, f_{avr} = average fitness values, $f_{\min}$ = minimum fitness values, $f_{\max}$ = maximum fitness values in $k-th$ generation, n is population size $\alpha = (U + L)/2$ and $\beta = (U - L)/2$. This idea is inspired by the idea of lifetime (Jin, 2003).

The fuzzification interface defines for each parent are the possibilities of being (Morrison and De Jong, 2001) Elderly, which are linguistic labels of both inputs. These values determine the degree of truth for each rule premise. This computation takes into account only one parent at a time and relies on the triangular membership functions as shown in Figure 2

Defuzzification interface

The Defuzzification interface computes a crisp value for the controlled crossover according to the linguistic labels $\{KP, UR, U, KPR, UKPR\}$, which are the outputs of the rule base and the triangular membership functions as shown in Figure 3. The fuzzification method used is

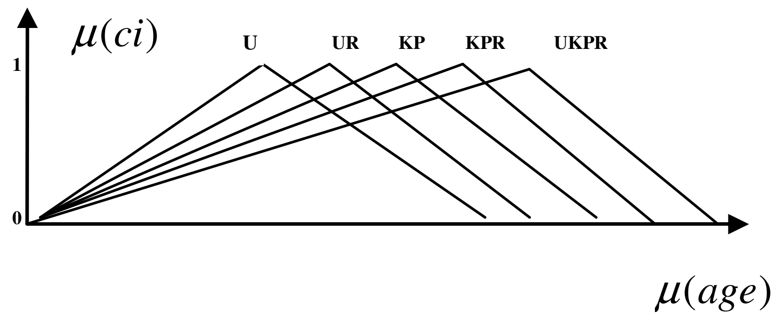

Figure 3. The crossover linguistic variable

Table 1. Test functions.

Test function	Constrains
$f_1(x)=\{1+(x_1+x_2+1)^2\cdot(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)\}\cdot\{30+(2x_1-3x_2)^2\cdot(18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)\}$	$-10.0\le x_i\le 10.0$
$f_2(x)=\left(4-2.1x_1^2+\frac{x_1^4}{3}\right)x_1^2+x_1x_2+(-4+4x_2^2)x_2^2$	$-3\le x_1\le 3$ $-2\le x_2\le 2$
$f_3(x)=\{\sum_{i=1}^{5} i\cos((i+1)x_1+i)\}\cdot\{\sum_{i=1}^{5} i\cos((i+1)x_2+i)\}$	$-10\le x_i\le 10$
$f_4(x)=\left(x_2-\frac{5.1}{4\pi^2}x_1^2+\frac{5}{\pi}x_1-6\right)^2+10\left(1-\frac{1}{8\pi}\right)\cos(x_1)+10$	$-5\le x_1\le 10$ $0\le x_2\le 15$
$f_5(x)=-\cos(x_1)\cdot\cos(x_2)/\exp((x_1-\pi)^2+(x_2-\pi)^2)$	$-10\le x_i\le 10$

center of gravity; the crisp value of the output variable is computed by finding the center of gravity under the membership function for the fuzzy variable (Klir and Yuan, 1995).

Crossover

This paper proposed three combine methods for cross-over based on binary encoding, such as combination of k-point cut, uniform crossover and random numbers. These random numbers help in finding high diversity of population in generation and to take better results for functions objective. Table 1 shows the comparison of methods for maximizing of six functions. Since the probabilities for mutations and crossover of the functions are fixed, so there might be some methods that don't have the best results. But in Multi-crossover by controlling systematically and using all the methods, the outcomes of the results are more accurate and reliable.

K-point cut, random selection (KPRS)

In this method, the first two parents are selected, then a positive integer number k is selected randomly, then these parents are divided into ($k+1$)-parts, after that k-part of these parts will be used for the offspring of the same k-point cut method and the other part of offspring is completed with random numbers of 0 or 1. Table 2 shows this technique for two points cut in offspring. The place of these parts can be changed randomly. These offspring have higher diversity in *genes* and since the placing of these parts can be changed randomly and the offspring have higher diversity in *genes*.

Uniform, random selection crossover (URS)

In this approach, the two parents are divided into two parts, in which one part of the offspring is completed using the uniform method of the parents and another part with random numbers of 0 and 1. Table 3 shows this technique in the offspring and the parts can be changed randomly.

Uniform, k-point, random selection crossover (UKPRS)

In this style, the two parents are separated in to k-parts,

Table 2. The technique for two points cut in offspring.

Parent 1	Parent 2	Randomly numbers

Table 3. The technique in the offspring.

Uniform method	Randomly number

Table 4. The procedure in offspring.

Uniform method	Randomly number	Parts of parents

in which one part of the offspring is completed with the uniform method of parents and another part with random numbers of 0 and 1 and the remaining place is completed by some parts of the parents. Table 4 shows this procedure in offspring. Position of these parts can be changed randomly. If the lengths of chromosomes are large, this technique is useful and they can find high diversity genes in offspring.

COMPUTATIONAL EXPERIMENT

Experiment design

In this section, the authors present the results for maximum of five different functions already in (Kirkpatrick and Ryan, 1991; Voigt et al., 1993) and compare the performance of this new scheme with commonly used crossover methods in solving this numerical function. All test functions have been solved with a constant population size, population size is 20 and probability crossover is = 0.50 and probability for mutation is = 0.02. Result of functions is listed in Table 1.

R is number of generation and r is average of 30 times run for taking results. The goal of using = 2000 is the comparison of methods to find better result. We can see three new methods in crossover; KPRS, URS and UKPRS have reasonable and usually better result for 2000 generation since the probabilities for mutations and crossover of the functions are fixed, so the methods might not have the best result. But in self-adaptation technique for 2000 generation, though probability of crossover and mutation are constant, the results always are better. When they consider = 2000.000 the goal is the comparison of prevention of premature convergence in these methods.

COMPUTATIONAL RESULTS

Result of functions is shown in Table 5. The Population size is 20 and probability crossover is = 0.50 and probability for mutation is = 0.02. R is number of generation and r is the average of 30 times run to take results.

Conclusion

In this paper, the authors proposed a technique for keeping diversity in the population based on sexual selection, fuzzy rules and multi-crossover. The result was a dynamic crossover controlled by fuzzy rules system that exhibited better performance than simple static GA. This indicates that the technique may be universally applicable to control GA in other optimization tasks. Synthesis of fuzzy logic to GA is still in its youth.

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Table 5. Population size is 20 and probability crossover is p_c =0.50 and probability for mutation is p_m = 0.02. R is number of generation and r is average of 30 times run for take results.

Functions	Crossovers	KP	UN	KPRS	URS	UKPRS	Self-adaptive
f_1	Result	8.176×10^{10}	7.015×10^{10}	8.255×10^{10}	7.961×10^{10}	8.255×10^{10}	8.270×10^{10}
	$R = 2\times10^3$	$r = 797$	$r \le 100$	$r = 1834$	$r \le 100$	$r = 1663$	$r = 1207$ r
	Result	8.284×10^{10}	7.015×10^{10}	8.277×10^{10}	8.071×10^{10}	8.255×10^{10}	8.284×10^{10}
	$R = 2\times10^6$	$r = 33488$	$r \le 100$	$r = 347724$	$r = 59559$	$r = 986838$	r=19068(
f_2	Result	158.306	110.2	162.9	113.043	162.898	162.9
	$R = 2\times10^3$	$r = 1215$	$r \le 100$	$r = 156$	$r \le 100$	$r = 1300$	$r \le 100$
	Result	162.9	162.9	162.9	162.9	162.9	162.9
	$R = 2\times10^6$	$r = 27876$	$r = 81302$	$r = 156$	$r = 96033$	$r = 2415$	$r \le 100$
f_3	result	110.163	136.515	203.428	146.206	167.098	210.459
	$R = 2\times10^3$	$r \le 100$	$r \le 100$	$r = 1620$	$r \le 100$	$r = 110$	$r = 1518$
	Result	209.45	139.515	210.481	146.206	209.34	210.482
	$R = 2\times10^6$	$r = 2567$	$r \le 100$	$r = 63027$	$r \le 100$	$r = 683045$	$r = 310075$
f_4	Result	285.513	203285	308.129	242.846	308.129	308.129
	$R = 2\times10^3$	$r = 1635$	$r \le 100$	$r \le 100$	$r \le 100$	$r \le 100$	$r \le 100$
	Result	303.242	212.833	308.129	281.908	308.129	308.129
	$R = 2\times10^6$	$r = 52564$	$r = 70209$	$r \le 100$	$r \le 100$	$r \le 100$	$r \le 100$
f_5	Result	8.880×10^{-3}	7.156×10^{-3}	8.908×10^{-3}	8.57×10^{-3}	8.569×10^{-3}	8.98×10^{-3}
	$R = 2\times10^3$	$r = 1584$	$r \le 100$	$r = 1748$	$r = 441$	$r = 440$	$r = 879$
	Result	9.005×10^{-3}	9.003×10^{-3}	9.004×10^{-3}	9.004×10^{-3}	9.006×10^{-3}	9.01×10^{-3}
	$R = 2\times10^6$	$r = 6224$	$r \le 100$	$r = 141282$	$r = 951919$	$r = 1277960$	$r = 278637$