IAMGA: Intimate-Based Assortative Mating Genetic Algorithm

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Abstract. Standard Genetic Algorithms (SGAs) is modeled as a simple set of fixed size individuals and each individual has no gender. The idea is based on non-random mating and important role of religious in the organization of societies. Essential concepts of religions are commandments and religious customs, which influence the behavior of the individuals. This paper proposes the Intimate-Based Assortative Mating Genetic Algorithm (IAMGA) and explores the affect of including intimate-based assortative mating to improve the performance of genetic algorithms. The IAMGA combined gender-based, variable-size and intimate-based assortative mating feature. All mentioned benchmark instances were clearly better than the performance of a SGA.

Keywords: Standard Genetic Algorithm, Gender-Based Genetic Algorithm, Gender, Assortative Mating, Intimate Relationship and Infusion Operator.

1 Introduction

Genetic Algorithms are the inspiration in the natural evolution. Over many generations, natural populations evolve according to the principles of “natural selection” and “survival of the fittest”. These principles were clearly stated by Charles Darwin in the Origin of the Species [1] and [2].

Genetic algorithms encode possible solutions for a problem as a “population” of simple chromosome-like data structures and apply recombination operators to these structures to generate “descendants” that are joined in new populations. If the solutions are properly encoded, each new generation contains “better adapted” chromosomes, optimizing the solution [3]. John Holland [2] established the basic principles of genetic algorithms.

Although GAs were introduced to modeling elements of natural evolution, one of the most crucial key, was left out. It was named gender. Through gender came the developing of sexual selection, a component of natural selection where reproductive success depends on interaction with a partner of the opposite sex to produce offspring [4]. The idea to exploit genders in genetic algorithms has been considered before in various publications, inspired by nature’s example [5].

Marriage is a concept to generate new generation in human religious communities; humans wed with different sex to generate new family. In these societies marriage with intimates is forbidden. This paper surveys new hypothesis in GAs. It describes a

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new relationship among genders called “Intimate Relationship” and defines new crossover mechanism for GAs. This mechanism is based on the religious marriage in human society that is the choice of a mate based on certain characteristics. To apply this mechanism, the population is divided into female and male genders.

The paper is organized as follow: Section 2 highlights IAMGA differences with respect to the classical Holland’s algorithm. In Section 3, some related work is presented. In Section 4, proposed new approach and the motivation of the IAMGA algorithm is presented. The obtained results and the comparison with the classical algorithm are shown in Section 5 and numerical experiments and results are presented.

2 Background

The GA algorithms are stochastic methods for searching and finding best solutions [6]. This section begins with describing Standard Genetic Algorithms (SGAs) and continues with some background on biological and social keys of human society such as intimate relationship and gender.

2.1 Standard Genetic Algorithms (SGAs)

John Holland first introduced SGAs for the formal investigation of the mechanisms of natural adaptation [2].Algorithm starts with a set of chromosomes called population. Solutions are taken and used to form a new population. Solutions are selected according to their fitness; the more suitable they are the more chances they have to reproduce, to form new offspring. It consists of three main operators: reproduction, crossover and mutation [7].

2.2 Intimate Relationship

In different divine religions people are forbidden to marry whose have an intimate relationship. Marriage with ancestor and child of ancestor is banned; such as uncles, nephews or nieces.

2.3 Gender

Male and female are different gender group in nature. Human cells contain 23 pairs of chromosomes for a total of 46. There is one pair of sex chromosome and the other pairs are autosomes. The Gender separation and sexual reproduction have been interest in many studies and application of genetic algorithm (GAs), since they are an important feature of the living organisms [8].

3 Related Works

Mate choice idea is not new and had been incorporated in SGA. Studies on Gender-based GAs can be found in [8-11] but usually the inclusion of gender is merely limited in multi-objective optimization or as a tag in the chromosome-preventing crossover with other individuals bearing the same gender flag.

Similarly, Ratford [12-13] and Ronald [14] both proposed selection schemes in which the first mate is selected using a traditional selection method, with the second mate being selected based on some seduction function between itself and the first mate.

Rejeb and Abuelhaija [10] proposed a method that adds the gender feature to chromosomes by representing "1" for male and "0" for female. They use a gendered genetic algorithm to solve graph-partitioning problems.

Song Goh, Lim and Rodrigues [15] proposed the new Sexual Selection Scheme. They suggest that mate choice in some species operates through female choice. They are determining the sex of individuals randomly or based on some problem-specific knowledge and involve the actual selection of a pair of individuals (one male and one female) hence the selection scheme would become problem dependant.

Parent-centric real-parameter crossover operators, proposed by Martinez and Lozano in [16], create the offspring in the neighborhood of the female parent by using a probability distribution and the male one defines the range of this probability distribution. The female and male differentiation process determines the individuals become female or/and male parents.

Vrajitoru [8] proposed four types of individuals: male (M), female (F), self-fertilizing (S-F), and hermaphrodite (H).

Ansotegui, Sellmann and Tierney [5] proposed to apply different selection pressure on the two gender populations. They apply intra-specific competition only in one part of the population and use Gender-based Genetic Algorithm (GGA) for the automatic configuration of solvers.

Wagner and Affenzeller [17] introduced a new sexual selection for Genetic Algorithms based on the concepts of male vigor and female choice of population genetics which provides the possibility to use two different selection schemes simultaneously within one algorithm.

4 Intimate-Based Assortative Mating Genetic Algorithm

In normal single/multiple-point crossover technique each mating of a couple of individuals creates a couple of offspring but in nature, in common, just mating of a couple of male and female individuals is allowed. Moreover in human religious community mating of species with intimate relationship is banned.

Although SGAs were introduced to modeling elements of natural evolution but there is no implicit notion of separate sexes but gender separation in SGAs is not a new idea. The main objective of this study is to show the performance of the gender based individual and intimate based mating.

The population of solutions consists of gender separation: male and female individuals. In the initialization, generate male and female individuals with equal probability 50% but over generations the numbers of male and female individuals are not equal.

In selection operation, mating couples are formed by selecting the individuals from the female/male population like in SGA. In crossover operation, the parents are chosen from the intermediate population by using the male selection. Crossover probability is used to measure which ones should be the parents. The parents consist of male and female individuals. If there is not non-intimate male individual for female then there are no offspring. When creating offspring, the male and female are chosen as parents. Crossover points are chosen randomly [15]. In mutation operation, the mutated individuals are chosen from the new population using equal mutation rates for male and female individuals.

The population of the intermediate population consists of new offspring. Individuals resulted from crossover and mutation operations in the previous generation. The male and female individuals are sorted according to objective function values or fitness values and rejected if individuals have low values.

In infusion operation, if the population is not balanced the new random chromosomes are infused to the next generation. The schematic of the IAMGA procedure is shown in Figure 1.

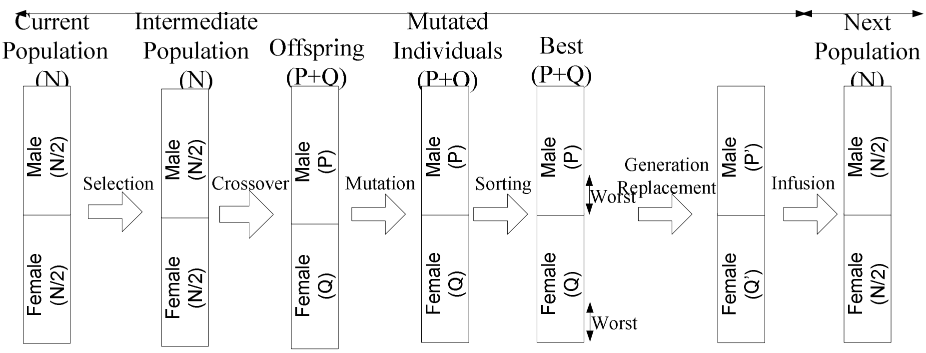

Fig. 1. A Schematic of IAMGA procedure

4.1 Representation

This study provides each individual with an additional feature:

- GenderBit: The sex or gender, as "GenderBit" with male and female values. "GenderBit" does not change in GAs operations such as mutation and crossover
- ID, FatherID and MotherID: unique ID to use for recognize intimate relationships

4.2 Crossover

The main difference among IAMGA and SGA is the method used for parent selection in the crossover operators. In SGAs individuals are mating randomly but in IAMGA with assortative mating two different sex parents are mating with extra condition. Mating requires one parent from each sex and parent should not have intimate relationship.

Females are selected in a sequential fashion without replacement which means that each female will only get to be selected for mating. For all unmated female select a male based on SGA selection operator. This process is repeated until all females have mated.

In two status parents have an intimate relationship. The first state is when selected individual ancestor is parent of current individual, or current individual ancestor is parent of selected individual. The second state is when current individual is ancestor of selected individual or selected individual is ancestor of current individual.

4.3 Infusion

The male and female mating constraint can lead the algorithm to deadlock in the case where the population becomes exclusively comprised of one of these two gender type, such that the reproduction is not possible anymore. This approach prevents these situations by infusion of new chromosome to population. Deadlock occurs when male/female population size is less than half of the initial population size. In deadlock IAMGA randomly infuses new male/female chromosomes to population.

```
Procedure IAMGA {
    t = 0;
    Random Initialize Male and Female Populations(t);
    /*with no preference for any of gender types*/
    Do{
       t = t + 1;
       Selection(t);
       Select_Mothers(t);/*From FemalePopulation(t);*/
       Do{
            Select_Fathers(t);/*From MalePopulation(t);*/
         }while(not intimate relationship between parent)
       Foreach(pair of parents in parents list)   {
         Perform crossover with probability Pc
         InsertNewMale(t);/*Into MalePopulation(t);*/
         InsertNewFemale(t);/*Into FemalePopulation(t)*/
         If (new offsprings are generated)
           Insert_FamilyTree(t);/*New offsprings*/}
       Mutation(t); /*preserving its gender*/
       Replacement(t); /*1-Elitism*/
       If (Male and FemalePopulation(t) are not balanced)
         Infusion(t);
       Delete_FamilyTree(t);/*Old familytree nodes*/
      }While (not termination condition are met)}
```

5 Experimental Results

To prove the concept of IAMGA, simulation studies were performed and applied to solve several test problems. For comparisons, IAMGA was compared with SGA. Selected benchmark functions are shown in Table 1. In Table 2, the proposed algorithm was tested on benchmark functions provided by CEC2010 Special Session on Large Scale Global Optimization [18-19]. Table 3 shows result for benchmark functions. Crossover and mutation methods are uniform and bit flip. Crossover and mutation rates set to 0.75 and 0.05. Replacement is 1-elitism generational method. Selection method is roulette wheel. The algorithm is conducted 20 runs for each test function. The same methods and parameter settings used for SGA and IAMGA. F8's best stability and convergence diagrams are shown in Figure 2.

This approach introduces a gender separation and a special "family tree" structure which indirectly defines intimate relationship among individuals.

Table 1. Benchmark function (F1-F12)

Name	Function	Limits
F1	$\sum_{1}^{3} x_i^2$	$-5.12 \leq x_i \leq 5.12$
F2	$\sum_{1}^{20} x_i^2$	$-5.12 \leq x_i \leq 5.12$
F3	$100(x_1^2 - x_2)^2 + (x_1 - 1)^2$	$-2.048 \leq x_i \leq 2.048$
F4	$\lvert x\rvert + \cos(x)$	$-10 \leq x \leq 10$
F5	$\lvert x\rvert + sin(x)$	$-10 \leq x \leq 10$
F6	$xsin(4x) + 1.1ysin(2y)$	$0 \leq x, y \leq 10$
F7	$\sum_{i=1}^{2}(x_i^2 - 10\cos(2\pi x_i) + 10)$	$-5.12 \leq x_i \leq 5.12$
F8	$\sum_{i=1}^{20}(x_i^2 - 10\cos(2\pi x_i) + 10)$	$-5.12 \leq x_i \leq 5.12$
F9	$1 + \sum_{i=1}^{2}\left(\frac{x_i^2}{4000}\right) - \prod_{i=1}^{2}\left(\cos\left(\frac{x_i}{\sqrt{i}}\right)\right)$	$-600 \leq x_i \leq 600$
F10	$1 + \sum_{i=1}^{10}\left(\frac{x_i^2}{4000}\right) - \prod_{i=1}^{10}\left(\cos\left(\frac{x_i}{\sqrt{i}}\right)\right)$	$-600 \leq x_i \leq 600$
F11	$2*418.9829 + \sum_{i=1}^{2} -x_i sin(\sqrt{\lvert x_i\rvert})$	$-500 \leq x_i \leq 500$
F12	$\sum_{i=1}^{2} 10^{i-1} x_i^2$	$-10 \leq x_i \leq 10$

Table 2. The results achieved by SGA and IAMGA on the test suite: Population size and number of generation set to 40 and 5000

Fun.	SGA		IAMGA	
	Mean	Std.	Mean	Std.
Shifted Ackley	2.01E+01	1.48E-01	**1.72E+01**	2.36E-01
Single-group Shifted and m-rotated Elliptic	4.28E+14	1.56E+14	**1.17E+14**	4.61E+13
Single-group Shifted and m-rotated Rastrigin	5.71E+08	6.57E+07	**3.05E+08**	6.50E+07
Single-group Shifted m-dim. Schwefel	1.38E+11	2.88E+10	**2.91E+10**	5.09E+09
D/m-group Shifted and m-rotated Elliptic	2.26E+10	1.55E+09	**1.90E+10**	1.66E+09
Shifted Rosenbrock	4.61E+11	7.99E+10	**2.38E+11**	4.20E+10

Practicable advantage of using IAMGA approach is using crossover operator with additional condition, which based on intimate relationship. It uses dynamic population and tries to simulate human nature behavior like gender separation, varied size and marriage. They are the most important advantage of IAMGA.

Experiment results show that IAMGA robustly provides better than SGA. The higher performance of IAMGA may be because that this algorithm maintains a higher genetic diversity in the population thus avoiding being trapped in local optima.

Table 3. Comparing IAMGA and SGA

Fun.	Population Size	Number of Generation	Optimum	SGA Mean	SGA Standard Deviation	IAMGA Mean	IAMGA Standard Deviation
F1	100	500	0	4.41E-02	5.38E-02	**4.45E-03**	1.34E-02
F2	500	1000	0	1.39E+01	4.34E+00	**7.54E+00**	2.88E+00
F3	80	300	0	1.50E-02	3.58E-03	**6.80E-04**	8.40E-04
F4	20	200	1	1.00E+00	6.50E-03	**1**	0
F5	20	200	0	2.50E-05	6.30E-05	**0**	0
F6	50	200	-18.5547	-18.1385	0.6816	**-18.3335**	0.4838
F7	80	1000	0	3.34E-02	8.32E-02	**3.40E-04**	2.60E-04
F8	100	5000	0	9.92E+01	1.38E+01	**3.61E+01**	1.76E+01
F9	100	800	0	1.60E-03	4.60E-03	**2.80E-04**	1.10E-03
F10	500	2000	0	3.44E+00	2.34E+00	**6.30E-02**	0.1397
F11	100	800	0	2.21E-01	4.09E-01	**4.88E-02**	5.39E-02
F12	50	1000	0	1.69E-02	3.02E-02	**3.50E-04**	1.00E-03

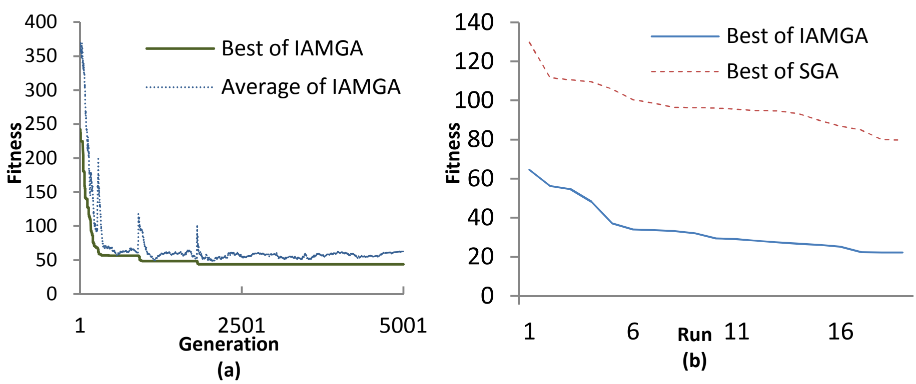

Fig. 2. (a) F8's Convergence Diagram (b) F8's Best Stability Diagram

6 Conclusion and Future Works

The main idea that helps IAMGA to improve its performance is using "Intimate Relationship" because relative individuals have the same ancestors which have many genes in common.

A practical advantage of using a population-based approach is that it can be parallelized naturally. We are currently working on an efficient parallelization of our code which will provide the practical basis for more nature based genetic algorithm. As future work, we are considering to locally improve individuals by purge duplicate individuals and replace them with "productivity".

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