A Priority based Parental Selection Method for Genetic Algorithm

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ABSTRACT

Selection is an important and critical aspect in evolutionary computation. This paper presents a novel parental selection technique that includes the advantages of both the deterministic and the stochastic selection techniques and helps to reduce the loss of diversity by distributing the reproduction opportunity among all the members of the population. Moreover, the proposed selection strategy promotes the concept of non-random mating by clustering the population into groups according to the fitness values and then by persuading the mating between individuals from different groups based on performance determined dynamically over the evolution. Computational results using widely used benchmark functions show significant improvements in the convergence characteristics of the proposed selection method over two well-known selection techniques.

Categories and Subject Descriptors

G.1.6 [**Numerical Analysis**]: Optimization—*Global optimization*

Keywords

Genetic/Evolutionary Algorithm, Selection Strategy

1. INTRODUCTION

Genetic algorithm (GA) is a heuristic search approach that uses the evolutionary concept of natural selection and genetics for optimization problems [1]. Different selection strategies affect the performance of a GA significantly. Deterministic selection methods ensure the participation of all the individuals by inducing each individual to be selected exactly once. On the contrary, probabilistic selection increases the robustness of a GA by inputting noise in it [1]. However, the GAs using some form of stochastic selection schemes are susceptible to "genetic drift" resulting in a loss of population diversity due to sampling variance [1]. The effect of this drift can be minimized either by using a selection scheme with smaller sampling variance or can be avoided all together by using deterministic selection methods. Moreover, the selection pressure induced by all the selection schemes available in literature is constant for the entire evolutionary process. Of the various selection strategies, *tournament selection*, *Roulette-wheel*, *Rank-based selection* etc. are widely used in evolutionary algorithms. A detailed description of these selection techniques is available in [2]. Here in this paper, we propose a hybrid parental selection mechanism that offers the advantages of both deterministic and stochastic selection paradigms. The selection of the first parent is done *deterministically*, while the second one is selected *stochastically* depending on the first parent. This non-random mating approach helps to reduce the loss of diversity by decreasing the sampling variance induced by the stochastic selections and intelligently distributes the reproduction opportunity among the individuals of the population.

GECCO'13 Companion, July 6–10, 2013, Amsterdam, The Netherlands.
ACM 978-1-4503-1964-5/13/07.

2. PROPOSED METHOD

The proposed parental selection scheme uses an asymmetric selection for choosing parents: a deterministic selection for the first parent ($Mate1$) and a stochastic selection for the second parent ($Mate2$). In this strategy, we begin by dividing the population into three groups G_b (Best), G_a (Average), and G_w (Worst) according to their fitness values. First mate ($Mate1$) is selected deterministically, while the selection of the second mate ($Mate2$) is accomplished by generating three mate pools Γ_a, Γ_b, Γ_w (where each pool is used to select *Mate2* for *Mate1* selected from a particular group). Each of these three pools are created by selecting m_b, m_a, m_w individuals randomly from G_b, G_a, and G_w respectively. The number of individuals m_b, m_a, and m_w are determined by developing two matrices i) *Priority Matrix* (Pr) and ii) *Weight Matrix* (W).

i) ***Priority Matrix (Pr)***: A 3x3 priority matrix Pr defines the priorities of three different groups G_b, G_a, and G_w to form the pools $(\Gamma_b, \Gamma_a, \Gamma_w)$. The columns of Pr denote three different priority levels: high, intermediate, and low respectively, while each row shows the groups having that priorities which are used for forming the mate pool Γ_i. $Pr_{i,j}$ denotes the group $G_{P_{i,j}}$ assigned the priority $P_{i,j}$ (=priority j for Γ_i).

ii) ***Weight Matrix (W)***: The 3x3 weight matrix W defines the weights that decide the fraction of individuals which are transferred to a given mate pool from different groups. In weight matrix, $W_{i,j} = \nu$ indicates the weight/probability ν for the group $(G_{P_{i,j}})$ with priority $P_{i,j}$. Now, we derive the weight vector W_i to create pool Γ_i for group G_i using $W_{i,1} = \frac{\alpha}{n_i}$, $W_{i,2} = \left(1 - \frac{\alpha}{n_i}\right) * q * \left\lfloor \frac{T_G}{T_{G_{max}}} \right\rfloor$, and $W_{i,3} = \left(1 - \frac{\alpha}{n_i}\right) * \left(1 - q * \left\lfloor \frac{T_G}{T_{G_{max}}} \right\rfloor\right)$. Here, n_i implies the total individual in G_i. We assign highest weight α/n_i to the group $G_{P_{i,1}}$ where parameter α and the proportionality factor q ensure the constraint $W_{i,1} > W_{i,2} > W_{i,3}$. $T_{G_{max}}$ and

Table 1: **Comparison of best Error values at N=10 and pop=100, after 1,000,000 fitness evaluation**

	EA1		**EA2**		**EA3(Proposed)**	
	Best	Avg±Std	Best	Avg±Std	Best	Avg±Std
F_{sph}	1.02E-2	8.17E+0±1.82E+1	1.01E-3	1.95E+0± 3.23E+0	2.54E-13	5.82E-9± 2.82E-8
F_{ack}	7.25E-1	1.64E+0± 1.01E+0	6.25E-1	1.71E+0± 7.13E-1	3.16E-1	7.27E-1± 3.49E-1
F_{grw}	9.10E-2	4.29E-1± 1.67E-1	5.59E-2	2.51E-1± 1.77E-1	3.40E-8	7.90E-2± 6.90E-2
F_{ras}	3.20E+0	1.78E+1± 9.81E+0	5.11E+0	1.12E+1 ± 5.35E+0	1.06E+0	3.29E+0± 1.80E+0
F_{ros}	1.88E+1	6.14E+3± 1.41E+4	7.94E+0	2.14E+1± 2.37E+1	4.29E+0	1.89E+1± 2.58E+1
F_1	2.69E+2	1.09E+3± 6.01E+2	1.78E+1	5.63E+1± 3.29E+1	2.97E-3	3.87E+0± 5.12E+0
F_2	1.28E+3	3.13E+3± 1.11E+3	5.41E+2	6.66E+2± 1.59E+2	2.35E+2	4.07E+2± 8.45E+1
F_3	5.93E+3	1.52E+4± 5.34E+3	3.81E+3	6.37E+3 ± 2.44E+3	9.82E+2	3.26E+3± 1.29E+3
F_4	4.29E+2	1.93E+2± 8.03E+2	3.40E+1	9.45E+1± 6.13E+1	7.48E-1	2.16E+1± 1.72E+1
F_5	5.94E+3	8.06E+3± 9.24E+2	5.69E+3	6.04E+3± 4.90E+2	3.37E+3	4.43E+3± 6.54E+2

T_G in the equations indicate the maximum possible group (=3 in our case) and total number of groups in current population.

Next, the three mate pools are created in every generation containing the same number of individuals (n_i) as that of the corresponding group according to the equation $\Gamma_i = \bigcup_{j=1}^{T_{G_{max}}} Pr_{i,j}[W_{i,j} * n_i]$. Once pools are created, we select the first mate ($Mate1$) for the reproduction operation deterministically, and based on $Mate1$ we select the pool from which $Mate2$ is chosen stochastically. The priorities are changed dynamically over the evolution based on a measure defining the crossover performance for a particular mating.

3. EXPERIMENTAL RESULTS

We evaluate the performance of the proposed selection algorithm using a test suite consisting of 15 benchmark functions namely F_{sph}, F_{ack}, F_{grw}, F_{ras}, F_{ros}, F_1 -F_{10}. More details of these benchmark functions are available in [3, 4]. For the sake of comparison, we have used three evolutionary algorithms: EA1, EA2, and EA3 using Binary Tournament, Roulette Wheel and our proposed selection scheme respectively as parental selection strategy. The experiments for all three approaches are carried out under the same evolutionary framework (cross-over, mutation, survival selection). The common EA parameters are chosen according to the values used in [3]. For EA3 (proposed selection), priorities of each group are initially set to ('b', 'a', 'w') and the minimum number of individuals (Δ) that must be contained in a group is set to one-fifth of the population size. Every method is executed for 1,000,000 fitness evaluations with 25 trials for each function. Although the evaluation has been performed for three different population size (*pop*= 50, 100, 200) with different dimensions ($N = 10, 30, 50$), the performances are shown here for ten benchmark functions only with $N = 10$ and $pop = 100$ in Table 1. We have shown the convergence graphs for F_{sph} (Fig. 1) and F_1 (Fig. 2) of three methods with N=30 and *pop*=50 for best case **Error** where the data for each method are plotted after every 50 fitness evaluations. From Table 1, it can be observed that the proposed selection method performs best for all functions both in terms of "best" and "average" values. Similar performance is observed for the other experiments with varying population and dimension size. A further illustration, on how the proposed model is improving the convergence characteristics

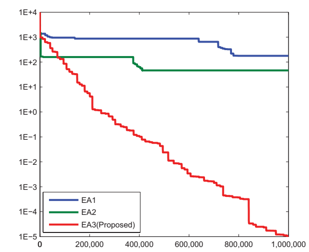

Figure 1: Convergence curves for F_{sph}

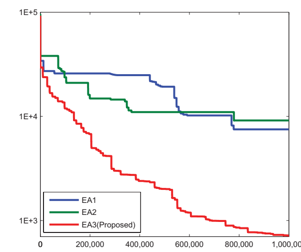

Figure 2: Convergence curves for F_1

of EAs, can be obtained looking at the convergence curves (Fig. 1 and 2). We found that, the proposed method exhibits gradual improvement in terms of error minimization. This gradual improvement exists in almost all the functions for EA3 which demonstrate the significance of dynamic priority and weight assignment for mate selection.

4. CONCLUSION

This paper introduces a new parental selection mechanism for cross-over operation in genetic algorithms that reduces the loss of population diversity by promoting non-random mating between individuals having different fitness values. We studied the efficacy of the proposed method using a test suit of 15 benchmark functions and significant performance improvement over two widely used selection mechanisms in terms of convergence characteristics has been observed.

5. REFERENCES

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