Lecture notes in computer science, Springer, Vol. LNAI 2275, pp.436-443, 2002.
Book•Advances in Soft Computing - AFSS 2002: 2002 AFSS International Conference on Fuzzy Systems. Calcutta, India, February 3-6, 2002. Proceedings

Parallelized Crowding Scheme Using a New Interconnection Model

P. K. Nanda[1],[1] D. P. Muni[2] and P. Kanungo[1]

[1]Department of Electrical Engineering
Regional Engineering College, Rourkela,
Orissa, India-769008
e-mail:pknanda@rec.ren.nic.in
[2]Electronics and Communication Science Unit
Indian Statistical Institute, 203 B. T. Road,
Calcutta, India-700 035

Abstract. In this article, a new interconnection model is proposed for Parallel Genetic Algorithm based crowding scheme. The crowding scheme is employed to maintain stable subpopulations at niches of a multi modal nonlinear function. The computational burden is greatly reduced by parallelizing the scheme based on the notion of coarse grained parallelization. The proposed interconnection model with a new crossover operator known as Generalized Crossover (GC) was found to maintain stable subpopulation for different classes and its performance was superior to that of the with two point crossover operators. Convergence properties of the algorithm is established and simulation results are presented to demonstrate the efficacy of the scheme.

1 Introduction

Genetic Algorithms (GAs) and Evolutionary Computation have been extensively used in different fields for solving complex optimization problems[1, 2, 3]. GA based class models have been developed to maintain stable subpopulations at the niches of a multi modal function[4] . Usually these class models are developed based on the notion of crowding and sharing. Although satisfactory results have been obtained by using GA, the major bottleneck is the high computational burden. Hence, the objective of designing parallel GA is two fold: (i)reducing the computational burden and, and (ii) improving the quality of the solutions. The design of parallel GAs (PGAs)involves choices of multiple populations where the size of the population must be decided judiciously. These populations may remain isolated or they may communicate exchanging individuals. This process of dividing the entire population into subpopulations and then providing the mechanism of interaction between them is known as coarse grained parallelism. The process of communications between individual demes is known as migration. The coarse grained PGA is broadly based on the island model and stepping stone model. In an island model the population is partitioned into small subpopulations by geographic isolation and individuals can migrate to *any* other subpopulation [5]. The takeover times in case of coarse grained Parallel genetic Algorithms have been investigated in [7].

[1]This work is supported by the MHRD project on Biomedical Image Processing Using Genetic Algorithm

In this article, a new interconnection model for the demes is proposed while attempting to parallelize the GA based crowing scheme. Our proposed PGA is based on the notion of coarse grained parallelization. This topology of the proposed model allows both intra demes and inter demes migration. Besides, a new crossover operator known as Generalized Crossover (GC) is proposed. The convergence analysis is carried out for the proposed scheme. Although, effect of migration policies, rate of migration, number of demes and size of the demes on the quality of the solution has been investigated, for the sake of illustration simulation results are presented only for the migration policy where the Good migrants of a demes replaces the bad migrants of other demes.

2 GA Class Models

Usually GA are used for function optimization and hence determining the global optimal solutions. In case of nonlinear multi modal function optimization, the problem of determining the global optimal solution as well as the local optimal solution reduces to determining the niches in the multi modal function. Thus the problem boils down to clustering the population elements around the given niches. Some effort has been directed in this direction for last couple of years where new strategies and algorithms are proposed[4, 6, 7].

2.1 Crowding Method

In the deterministic crowding, sampling occurs without replacement [4]. We will assume that an element in a given class is closer to an element of its own class than to elements of other classes. A crossover operation between two elements of same class yield two elements of that class, and the crossover operation between two elements of of different class will yield either ; (i) one element from both the classes, (ii) one element from two hybrid classes. For example, for a four class problem, the crossover operation between two elements of class AA and BB may result in elements either belonging to the set of classes AA, BB or AB, BA. Hence, the class AB offspring will compete against the class AB parents, the class BA offspring will compete with class BA parents. Analogously for a two class problem, if two elements of class A get randomly paired, the offspring will also be of class A, and the resulting tournament will advance two class A elements to the next generation. The random pairing of two class B elements will similarly result in no net change to the distribution in the next generation. If an element of class A gets paired with an element of class B, one offspring will be from class A, and the other from class B. The class A offspring will complete against the class A parent, the class B offspring against the class B parent. The end result will be that one element of the both classes advances to the next generation no net change.

3 Interconnection Model

Besides migration policy, migration rate also affects the rate of convergence. A good migration policy with optimum migration rate may not always yield optimum solutions because the rate of convergence and the quality of solution also depends upon type of interconnection structure of the island model.

Figure 1 shows the proposed interconnection model for a four deme model where the self loop allows intra deme migration and the other connections among demes allows inter deme migration. The new model is fully interconnected in the sense that intra deme and inter deme exchanges are allowed. The intra deme migration accelerates the convergence because it allows the proportion of the good individuals to grow rapidly. In a model consisting of more than four demes, each deme is connected to every other deme in the interconnection topology. Thus the proposed model is a fully connected hybrid model based on the notion of Island model with the exception that the neighboring demes take part in migration.

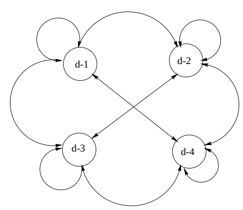

Fig.1: Proposed Interconnection Model for 4 demes

3.1 Generalized Crossover Operator

We propose a new crossover operator known as *Generalized Crossover Operator (GC)*, which when applied to two parents produces one offspring instead of two offsprings in the Basic Genetic Algorithm. The operator can be described as follows. The two parents p_1 and p_2 are selected at random and the two crossover points are also selected at random. In between the two crossover points, two bits of the respective positions of the two selected parents are now passed through a switching function to produce one output. For two variables case, a switching function is selected at random from the 16 possible functions and the two bits are impressed as the input and the corresponding output is stored in the same bit position of one of the parents. Analogously, all other bits are generated by selecting the other respective bits from the two parents and passing through the randomly selected switching function. Hence, a stream of bits between the two crossover points is generated that replaces one of the parents to generate one offspring. The motivation is two fold: (i) it helps to examine the diversity of solutions in the solution space, (i) this model is more plausible from the evolutionistic sense that two parents produce one offspring at a time. Same GC operator is applied to the same two parents with the two new randomly chosen crossover points and the necessary switching function to produce one more offspring. As a result of this operation two offsprings are produced fro the two parents by applying the GC operator twice. This process may be repeated to produce M offsprings form N parents. In order to maintain the total population of elements constant over generations M is equal to N.

4 Algorithm

The steps are the parallelized Crowding scheme are the following.

1. Initialize randomly population elements of size N.
2. Divide the population space into fixed number of sub-populations and determine the class of individual in each sub-population.
3. i. In the given sub-population, choose two elements at random for Generalized Crossover (GC) and mutation operation.
   ii. Evaluate fitness of each parents and offspring.
   iii. The tournament selection mechanism is a *binary tournament* selection. Among the two parents and offsprings, the set which contains the individual having highest fitness among the four cements is selected to be the set of parents for the next generation.
   iv. Repeat steps (i), (ii), and (iii) for all the elements in the sub-population.
   v. Repeat step (i), (ii), (iii) and (iv) for a fixed number of generation.
4. Step (3) is repeated for each sub-population.
5. Migration is allowed from each deme to every other deme. The individuals are migrated based on the selected migration policy. Numbers of elements to migrate are determined from the selected rate of migration. The elements migrate with migration probability P_{mig}. At last some percentage of individuals of one deme replace the same percentage of individuals of the same deme, this self migration is valid for all demes with a probability of migration P_{smig}. The individuals migrated in self-loop are based on the selected migration policy.
6. Repeat steps 3, 4, and 5 till convergence is achieved. The algorithm stops when the average fitness of the total population is above preselected threshold.

Theorem 1 *Assume P_{k-1} to be the proportion of good individuals after $(k-1)^{th}$ migration, Then for any arbitrary initial condition with P_0, the algorithm converge for*

$$P_{k-1} = (1 - \delta_k)^{\frac{1}{N}}$$

where, $N = s^n$, s=Tournament size of tournament selection method, n=Number of generations between two consecutive migrations and , δ_k = Proportion of good individuals taking part in k^{th} migration.

Proof:

In the whole population of mixed fitness, we assume an element to be a *good* individual if its fitness is above a threshold and *bad* if the threshold is below a threshold. Thus in the whole population each individual may be either good or bad. Let the individuals be selected to the next generation using tournament selection. In tournament selection a random sample of s individuals is selected and out of these s participants one best individual is selected. If all the s participants are bad and since one individual is to be selected so the selected individual is a bad individual. Thus a bad individual will survive only if all the s individuals are bad.

If the initial proportion of good and bad individuals are P_0 and Q_0 respectively, then the proportion of bad individuals in the next generation is:

$$Q_1 = {Q_0}^s \tag{1}$$

(1)implies that $Q_2 = (Q_1)^s = ({Q_0}^s)^s = {Q_0}^{s^2}$. Therefore, at the n_{th} generation, $Q_n = {Q_0}^{s^n}$. Let the first migration be allowed after n generations. Then the Proportion of bad individuals after first migration or in other words after n generations can be expressed as $Q_{1n} = {Q_0}^{s^n} - \delta_1$. Where δ_1 = Proportion of bad individuals replaced by good migrated individuals after first migration. It can be shown that the Proportion of bad individuals after k^{th} migration or kn generations.

$$Q_{kn} = Q_{k-1}^{s^n} - \delta_k \tag{2}$$

Where δ_k =Proportion of bad individuals replaced by good migrated individuals by k^{th} migration.

Since there are only two types of individuals i.e. good and bad, so the sum of proportion of good and bad individuals is always unity.

The algorithm will converge to the desired solution when all individuals are good individuals or the proportion of good individuals P_{kn} is unity . This implies that the proportion of bad individuals is zero. Thus for convergence $Q_{kn} = 0$

Since, δ_k is the proportion of good individuals taking part in k_{th} generation, so

$$\delta_k \geq 0 \tag{3}$$

Substituting (3) in (2),we have

$$Q_{kn} \leq Q_{k-1}^{s^n} \tag{4}$$

Since Q_{k-1} is a proportion ,from (4) it is evident that the population of bad individuals has a monotonically decreasing trend. This implies that the population of good individuals will have an increasing trend. From(2), we have $Q_{k-1}^{s^n} = \delta_k$. This implies that $P_{k-1}^{s^n} = 1 - \delta_k$ or $P_{k-1} = (1 - \delta_k)^{\frac{1}{N}}$. Hence, proved. The theorem provided a bound on the proportion of good individuals taking part in migration among the demes.

5 Simulation

For the sake of illustration, We have considered the four class problem given by the following functions; $f(x) =\mid Sin4\pi x \mid \quad 0 \leq x \leq \ 1$ and $f(x) =\mid e^{2.0(x-0.125)} Sin4\pi x \mid$ $0 \leq x \leq \ 1$. The parameters used are: Total Number of population elements N=400, Number of demes=4, Probability of Crossover=0.8, Probability of mutation=0.001, Probability of migration $p_{mig} = 0.9$, probability of self migration $P_{smg} = 0.9$, rate of migration=20%, and the threshold of fitness for the stopping criterion=0.98. In our simulation we have employed only Good-Bad migration policy. Simulation was carried out 40 times with different initial sampling and the average of the 40 experiments is presented. The population of element converged to their respective peaks as shown in Figure 2. The performance of the algorithm with the new model and with the proposed GC operator was compared with model employing two point crossover operator as shown in Figure 3. It is clear form Figure 3 that the algorithm converges faster than that of the model employing two point crossover operator. The performance of the algorithm depends upon the proper choice of rate of migration as shown in Figure 4. From Figure 4 it is clear that as the migration rate increases from 8% to 40% the convergence time decreases and again increases as the migration rate is increased to 56%. The population distribution for the decaying sinusoidal function is shown in Figure 5. It is clear from Figure 5 that the algorithm maintained stable subpopulations in the respective peaks even if the niches are of different heights. In this case also the model with GC operator outperforms to that of the two point crossover operator. This effect for each class is exhibited in Figure 6. The effect of rate of migration is also presented in Figure 7 where it is clear as the rate increases form 8% to 20% the time of convergence decreases and it shows again an decreasing trend if the rate is further increased to 32%.

6 Conclusions

A new interconnection model with a new crossover operator is proposed for parallelizing the crowding scheme for maintaining the subpopulations in respective classes. Thus a new parallel Genetic Algorithm Based Class model is proposed for classification. The efficacy of proposed algorithm is better than that of the algorithm with other models. Convergence analysis is carried out and is shown that the algorithm converges for an optimum rate of migration. The results presented are the serial implementation of the parallel algorithms. Attempts are made to obtain results with parallel implementation.

References

[1] Goldberg,D.E. *Genetic Algorithm in Search, Optimization and machine learning*, Addison-Wesley, (1989).

[2] T. Back, D. B. Fogel and T. Michalewicz, (Ed.): Evolutionary Computation 1; Basic Algorithms and operators, Institute of Physics publishing, Bristol and Philadelphia (2000)

[3] Chellapilla Kumar: Combining Mutation Operators in Evolutionary Programming, IEEE Transaction on Evolutionary Computation, Vol.2, No.3, (1998), pp.91-96.

[4] Mahfoud,Samir.W.: Simple Analytical Models of Genetic Algorithms for Multi modal Function Optimization,Technical Report .Illinois Genetic Algorithm Laboratory, IlliGAL Report No.93001, Feb.(1993).

[5] Cantu-Paz,E.: A summary of Research on Parallel Genetic Algorithms, IlliGAL Report No.95007, July (1995).

[6] Cant-Paz,E.: Designing Efficient and Accurate Parallel Genetic Algorithms, parallel Genetic Algorithms, Ph.D. dissertation, Illinois Genetic Algorithm Laboratory, UIUC, USA, (1999).

[7] Cant-Paz,E.: Migration policies and takeover times in parallel Genetic Algorithms, Proceedings of the International Conference on Genetic and Evolutionary Computation, San Francisco, CA, (1999), pp.775-779.

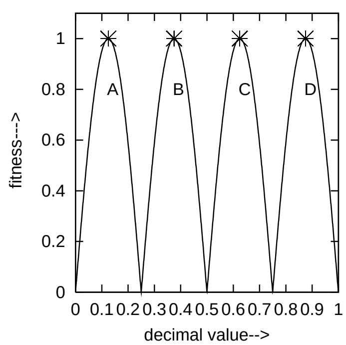

Fig.2: Good-Bad migration policy, A=93,B=93,C=106,D=108, generation=20

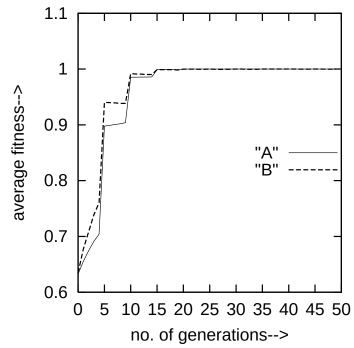

Fig.3: Good-Bad Migration policy A for GC and B for Two-point Crossover, migration rate: 8%interdeme 8%intrademe

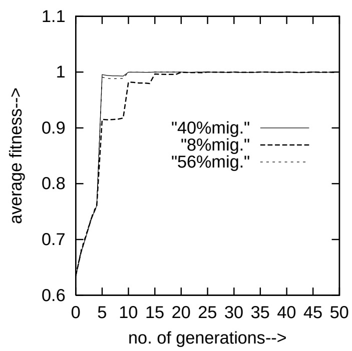

Fig.4: Effect of rate of migration for Good-Bad Migration policy

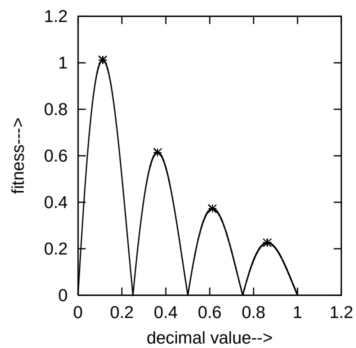

Fig.5: Good-Bad Migration policy,A=90,B=113,C=106,D=91, GC operator.

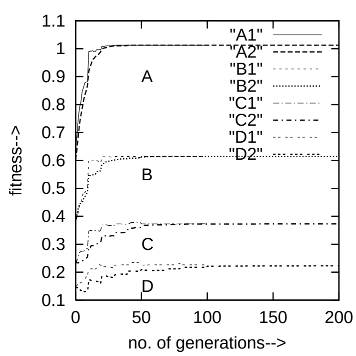

Fig.6: Good-Bad migration policy, A1,B1,C1,D1 for GC operator, A2,B2,C2, D2 for Two point Crossover.

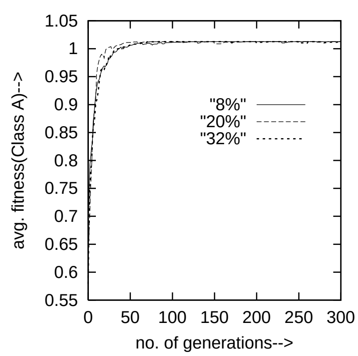

Fig.7: Effect of rate of migration, Good-Bad Migration policy,8% intrademe migration.