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PARALLEL GENETIC ALGORITHM

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ABSTRACT

Genetic Algorithms are modern and powerful search techniques that have been used successfully to solve difficult problems in optimization, neural networks, pattern recognition, robotics and data mining etc. The problem of premature convergence of simple GA led the research towards the implementation of various Parallel Genetic Algorithms to achieve a balance between exploration and exploitation of the search space. The main objective of this paper is to review and present the important research works in PGAs in a unified manner. To point the possible direction for further research, the paper also highlights the unresolved problems that have remained unaddressed or have not been studied in a systematical manner. After giving the initial benchmark studies, the main focus is on relatively recent research advances. Finally, a parallel and promising Gradual Distributed GA and Hierarchical Genetic Algorithms is discussed, using crossover and migration operators having different degree of exploration and exploitation, to solve the difficult search problems.

Keywords: Parallel Genetic Algorithms, Master-Slave Genetic Algorithms, Distributed Genetic Algorithms, Gradual Distributed Genetic Algorithms, Hierarchical Genetic Algorithms.

I. INTRODUCTION

GAs are generally applied to difficult and bigger problems where other methods of finding adequate solutions fail due to their high algorithmic complexity. The two important factors to measure the performance of GA are the quality or accuracy of the solution and the time needed to reach the solution of required accuracy. The simple GAs were soon stretched to their limits in case of some rather difficult search spaces. To reach a reasonable solution for a problem, the GA needs to keep a balance between exploitation and exploration. To reach a global optimal, it is essential to have enough diversity of sampling points in the search space and then refine the solution focussing on individuals of higher fitness. Many a times, this balance of exploration and exploitation is very difficult to reach and simple GA ends up converging in a local optimal solution. This is known as problem of **premature convergence** [1-5]. Some tools like different selection schemes, scaling, ranking, dynamic and optimized parameters setting have been suggested to avoid premature convergence [6,7]. The solutions suggested could improve the diversity by varying selection pressure but could not eliminate the problem of premature convergence. Parallel or Distributed GAs have become the most important method to maintain the diversity based on spatial separation. [8-10]. DGA preserves the diversity due to semi-isolation of sub-populations.

This paper is an attempt to present the some of the most important, relevant and relatively recent research done on parallel GAs and to highlight the unresolved problems. Though all kind of parallel GAs are introduced, however, the paper focuses on distributed GAs and Hierarchical GAs. The research work done in this field is enormous and the popularity of Parallel GAs has picked up at greater speed. Therefore, the paper includes only those research work that are considered important someway and have contributed to the growth of field of Parallel GAs and some of the problems posed in those papers are still an open area of research.

II. THE PARALLEL GENETIC ALGORITHMS

The basic idea behind most parallel programs is to divide a task into smaller pieces and solve the pieces simultaneously using multiple processors. The general idea to parallelize a GA is to divide the population into several sub-populations, each one of them is processed by a GA independently from the other. The operator migration produces exchange of genetic material between the sub-populations.

There are mainly five types of parallel GAs based on their method of parallelization.

- Global Single population Master-Slave Aas
- Single population Fine-Grained GAs based on Spatial Structure
- Multiple-Populations Distributed GAs
- Gradual Distributed GAs
- Hierarchical GAs.

2.1 Global Parallelization: Master Slave Gas

The evolution of fitness and sometimes the application of operators are carried out in parallel. In this, the fitness evaluation for sets of individuals could be assigned to different processors. The communication occurs only at the start and at the end of the phase. This can be done in master slave fashion, where master is responsible for synchronization i.e. sending the individuals to the other processors for evaluation, collecting the results and applying the genetic operators to produce next generations. Global parallelization does not change the overall nature of the GA but a speedup proportional to the number of processors minus the cost of communication is expected. Almost all the work in Master Slave parallelization has reported sub-linear speed-ups due to the communication cost [11-13].

2.2 Fine Grained Ga

In this model the population is divided into large number of small size populations. In extreme case a single individual could be assigned to one processor. They are also known as massive parallel GA. The fine-graineded GA has spatial structure that limits the interactions between the individuals and selection mechanism and crossover operator are only applied to the neighbouring chromosomes. Every chromosome selects the best neighbour for recombination and resultant individual shall replace it. Since the neighbourhood overlaps, good solutions may disseminate across the entire population. These are also known as cellular GA and implemented on massive parallel computer [15-23]

2.3 Distributed Genetic Algorithms

In case of Distributed Genetic Algorithms, the population is divided into small sub-populations that are processed on different processors. Each sub-population evolves independently and simultaneously. Periodically, migration operator exchanges individuals among the sub-populations. The Distributed GAs are also known as Coarse Grained GAs These are the GAs that have got special attention from researchers due to their easy implementation and capabilities to find better solutions. Some of the important work in this area is summarized below.

2.3.1 Related Work

Grasso, in his dissertation work simulated the diploid individuals (there were two sub-components for each gene) by dividing the population into five demes. The demes exchanged the individuals at fix intervals. He tried several migration rates and noticed the rate of improvement of average population fitness was faster in the smaller demes than in a single large population. Tanese, did an important work on a parallel implementation of Course Grained GAs, where demes used a hypercube topology to communicate with other demes. The migration occurred at fix interval of time along one dimension of the hypercube. The best individuals migrated to the neighbouring population replacing the worst in the target population. Cohoon, Hedge, Martin and Richard noted certain similarities between the evolution of solutions in the parallel GA and the theory of punctuated equilibria. When the environment changes, there is rapid evolutionary change. An important component of the environment of a population is its own composition because individuals in a population must compete for resources with the other members. Therefore, the migration of individuals from other population can punctuate the equilibrium and trigger evolutionary changes.

2.4 Gradual Distributed Gas

GDGAs are a class of heterogeneous DGAs based on real coding in which sub-populations are distinguished by applying crossover operators with different degree of exploration and exploitation. By doing this, a parallel multi-resolution is obtained with regard to the crossover operator that allows a spread search (exploration) along with an effective local tuning (exploitation) to be simultaneously achieved. In this model, sub-populations must be adequately connected for exploiting the multi-resolution in a gradual way. This offers refinement or the expansion of the best zone so far emerged. The migration between sub-populations belonging to different categories produce these final effects. The basic structure of GDGAs is shown in fig 1. They are based on hyper-cube topology with three dimensions with two important sides to be differentiated.

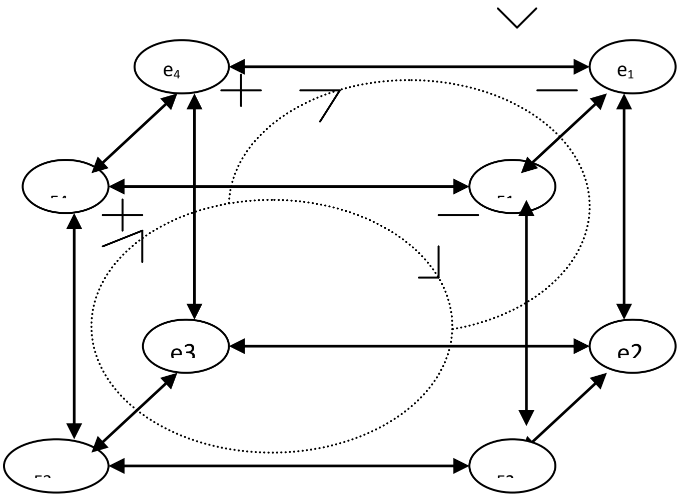

Figure1: GDGA Cubetopology

The front side is devoted to exploration. It is made up of four sub-populations E1 to E4, to which exploratory crossover operators are applied. The exploration degree increases clockwise starting at the lowest E1 and ending at highest E4. The rear side is for exploitation. It is composed of sub-population e1 to e4, that undergo exploitative crossover operator. The exploitation degree increases clockwise starting at the lowest e1 and finishing at the highest e4.

2.5 Hierarchical Gas

Recent and one of the latest development in the field parallel GA is the creation of Hierarchical GAs. The fact that there is an optimal number of demes, limits the processors that can be used to reduce the execution time. Using more than the optimal number of demes is wasteful and would result in slower algorithm. Hierarchical parallel GAs can use more processors effectively and use the execution time more than the pure multiple deme GA. Hierarchical GAs have been produced by combining any of two methods to parallize GAs. At the upper level most of the hierarchical GAs are multi deme GAs. At the inner level they can use any other method of parallel GAs.

2.5.1 Related Work

Gruau implemented Hierarchical GA in which each deme was placed on a 2-D grid and demes themselves were connected as 2-D torus. Migration between demes occurred at regular intervals and good results were reported for a novel neural network design and training application Gordon updated ASPARAGOS and its ladder structure was replaced by a ring and it maintains several sub-population that are themselves structured as rings. Migration across sub-populations is possible, when a deme converges it receives best individual from other deme.

2.5.2 Hierarhical Distributed Gas

Another popular method of hybridizing parallel GAs is to use multi-deme GA at both upper and lower level. The idea is to force mixing at the lower level by using high migration rate and a dense topology while a low migration rate is used at high level. The remaining of the paper is dedicated to Hierarchical Distributed GA which is of considerable importance in the advances that have taken place recently. The main idea of these algorithms is to connect DGAs with other DGAs and this way we get a DGA whose nodes are again simple DGA. In figure2 below, a hierarchical Distributed GA, with a cube topology,

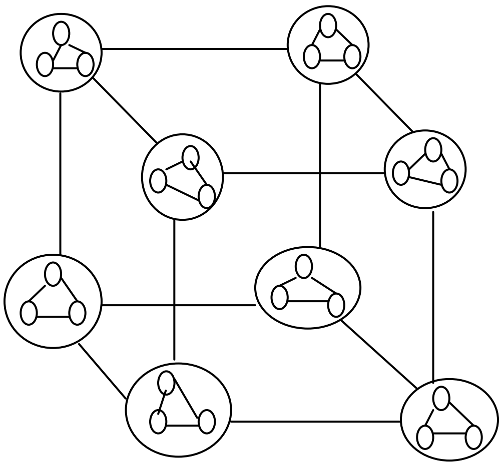

Figure2: HDGA with a Cube Topology

2.5.3 Hierarchical Gradual Dgas

Hierarchical Gradual DGAs are Hetrogeneous HDGAs based on homogeneous basic DGAs .Herrea and Moraga implemented Hierarchical GDGA in which they applied a homogenous DGA to every node of GDGA. They applied the different crossover operator with different degree of exploration and exploitation to the nodes of GDGAs.

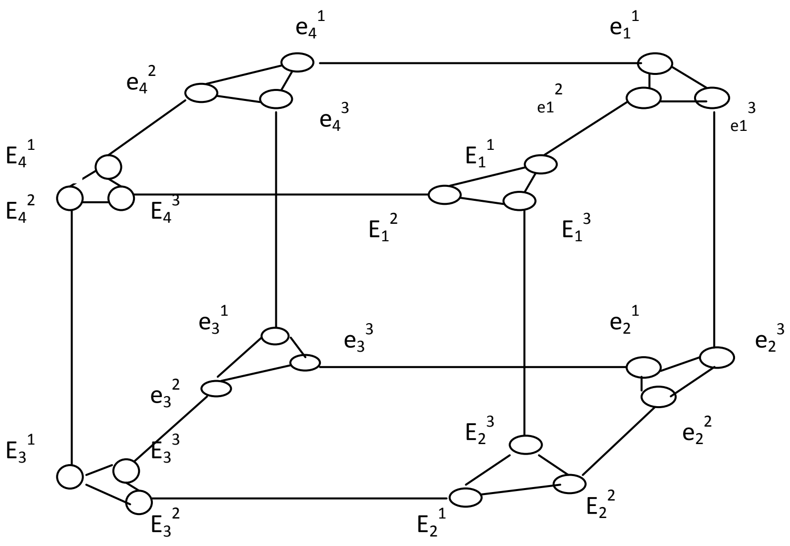

Figure 3: Hierarchical GDGA

IV. SUMMARY AND CONCLUSIONS

This paper has presented a review of impotant and representative research work on parallel genetic algorithms. From the research work given above, it is concluded that multiple deme GAs are almost an extension of serial GAs as far as implementation of deme GAs is concerned. There is relatively little effort required to convert serial GA into a multiple deme GA but the gain in performance is relatively high. This review has contributed numerous examples that show that Parallel and Hierarchical GAs are capable of combining speed and efficacy. We have successfully served the purpose to introduce five kinds of parallel GAs, related research work and indicated the possible direction of future research by identifying the unresolved problems in this area. We have given some theoretical work done for DGAs but this is not enough to explain all the mysteries of how PGAs work? All the above theoretical work makes very simple assumption, does not included all the complexities and leaves many issues unresolved. The GDGA and HDGA are class of parallel GAs, whose behaviour get affected with many more parameters, have added extra complexity to the already compounded scene of simple DGAs.

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