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Improved Performance of Replacement Strategies in GA

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Abstract-Genetic algorithm is blind global search technique based on population and exploiting objective function. Genetic algorithm works on set of individual, not on single solution.After applying reproduction and mutation operator'sreplacement strategy is executed.This paper discusses various replacement strategies to help in selecting suitable replacement class(generational and steady state), which we apply over the basic steps i.e. selection, crossover, mutation. Steady state replacement helps in enhancing the performance of genetic algorithm as it propitiates useful diversity.

Keywords-fitness, generationgap, genetic algorithm, replacement, steady state

I. Introduction

Genetic algorithms[1] are powerful and widely applicable stochastic search and optimization method based on the concept of natural evaluation(Darwin's theory) that follows the principal of survival of thefittest [2]. Genetic algorithm helps in solving the problem optimally within a defined search space with the help of population(offspring) from old one. These searches through the state spacehaving no knowledge reference,by intelligently exploiting only coding and objective function in each generation. Genetic algorithm can handle complex problems as disjoint feasible space, complex solution space but not very efficiently. So use of hybridization with other techniques may improve the search efficiency.GA works onElitism which speeds up the performance of genetic algorithm. In a breeding cycle after reproduction and mutation replacement is the last stage. Once offspring are produced, a method must determine which members of the population should be replaced by the new solutions. Method for replacement is generational update(delete all) and steady state updates (based on ranking).

GA works on the population of fixed length strings called chromosomes which are made up of genes and based on gene values (alleles)[3], fitness value is associated with each chromosome. Having a specific objective function and constraints we select either an individual is best or worst. Best one is selected as parent afterwards.

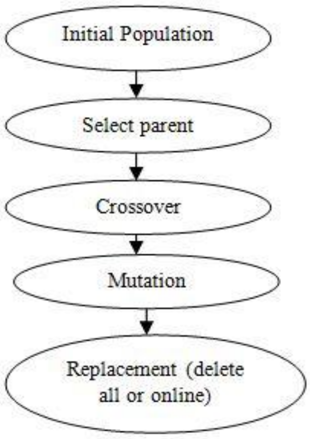

Figure 1 Simple genetic algorithm

Crossover and mutation are used to maintain balance between exploitation and exploration. At the final step i.e. during replacement, the old individuals are replaced by some new off-springs. In this scenario, elitism solves the problem of pre-convergence by directly copying the best individual into the next generation without any changes.

II. Replacement

Replacement incorporates the new candidate solution in the population, help in exploration of search space.Basically, there are two types of GAs commonly used;characterized by the type of replacement strategies they use. A Generational GA uses a (μ,μ) replacement strategy where the offspring replace the parents.Simple or generational GAs replaces entire population, per the dictates of the selection scheme.A Steady-State GA usually will select two parents; create 1-2 offspring which will replace the 1-2 worst individuals in the current population even if the offspring are worse than the individuals they replace.SSGAs are overlapping systems, because parent and offspring compete for survival. SSGA has higher selection pressure,which help in increasing the performance.

Replacement schemes:

1. Generational replacement or Full replacement
    - Basic update
    - Derived (λ,μ) and (λ+ μ,μ) update
2. Steady state GAs use different replacement schemes
    - Replace Worst.
    - Replace Random.
    - Replace Parent.
    - Replace most similar (crowding).
    - Replace Best.

Only replace worst and replace most similar aregenerally very effective (when replace parent works, it is because parents are similar)[4]. Above scheme can be modified by using Elitism or tournament as

RR (Replace random)
RRB (Replace random if better)
RR E (Replace random with Elitism)
RRKT (Replace after Tournament between two random individual)
RRKTB(Replace after Tournament between two random individual if better)

Solving ONE-MAX problem using generational replacement scheme

String No.	Initial Population Generated randomly	F(x) One max	Tournament Selection	Selected
1	10000	1	10000 vs 10111	10111
2	10111	4	10111 vs 01101	10111
3	01100	3	01100 vs 10000	01100
4	01101	2	01101 vs 10000	01101

Figure 2: Tournament selection is applied to select parent.

In figure 2 Initial population is generated randomly, its fitness is calculated using objective function "one max" and parent is selected by carrying out Tournament selection. Parents are then shuffled and one point crossover is applied with bit flip mutation. In the last basic generational updates (delete all) are used for replacement.

String No.	Selected Population	Shuffled Parents	Crossing Point	After crossover
1	10111	10111	2	10111
2	10111	01100		10100
3	01100	01101	1	00111
4	01101	10111		11101

Figure3: Offspring generated using 1-point crossover

After crossover	Mutation Bit flip	F(x) onemax	Offspring Population	Replacement (Replace all)	New population
10111	10110	3	10110	10110	10110
10100	10101	3	10101	10101	10101
00111	10111	4	10111	10111	10111
11101	11100	3	11100	11100	11100

Figure4: New population obtained by applying generational update

Basic generational replacement producing N offspring from a population of size N to form the population at the next time step(generation) and off-springs completely replaces the parent selected.The Process of generational update is

1. Selecting six parents,
2. Allowing the parents to create offspring,
3. Mutating the six offspring,

4. Evaluating the offspring, and
5. Replacing the parents with the new offspring.

Is repeated until a stopping criterion has been reached. Stopping criterion can benumber of generations,fitness has reached a plateau, amount of time, minimum fitness, threshold satisfied.

Steady-State GAor online GA use an ordinal based method (base on ranking) for both the selection and the replacement, usually tournament method.New individual is inserted as soon as they are created. Insertion of new individuals forces for replacement of another population member. Some overlap exists between populations of different generations. Amount of overlap between the current population and new population is Generation Gap that is replaced each cycle. A generation gap of 0.9 means that the 99%population is replaced by the offspring. Ageneration gap of 0.05 (given a population size of 100) means only five individual is replaced.This process of:

1. Selecting two parents,
2. Allowing them to create two offspring, and
3. replacing the two worst individuals in the population with the offspring Is repeated until a stopping measure is reached.

Notice that on each cycle the steady-state GA will make two function evaluations while a generational GA will make P (where P is the population size) function evaluations.Therefore, you must be careful to count only function evaluations when comparing generational GAs with steady-state GAs. In Replace Worst (Elitism) deleted individual is the worst member of population. Assume that offspring population is smaller than original population. Deletion of worst member increases the selection pressure but this is quite radical. Replace worst is effective replacement strategy that helps in optimizing the solution quickly. This is one of the elitist scheme [5]. In random replacement, children replace two randomly chosen individuals in the population. The parent are also candidate for selection. Parent selection is useful for continuing the search in small population, since weak individuals can be introduced into the population. In replacement with most similar (crowding) both offspring obtain by mating and mutation are kept. [3] The first offspring is compared to these solutions and replaces the member that is most similar. The same procedure is followed for the second offspring. This means that there is a small, but finite probability that second offspring replace the first. In weak parent replacement, a weaker parent is replaced by a strong child.After reproduction only the fittest two, parent or child, return to population. After generations the overall fitness of the populationimproves when paired with a selection techniquethat selects both fit and weak parents for crossing, but if weak individuals anddiscriminated against in selection the opportunity will never raise to replace them [7]. Both parents replacement is simple. The offspring replaces the parent and eachindividual only gets to breed once. As a result, the population and genetic materialmoves around but leads to a problem when combined with a selection technique thatstrongly favors fit parents: the fit breed and then are disposed of.

Population diversity and selection pressure are primary factors to effect optimization of problem. Without selection pressure search becomes random and lack of diversity cause premature convergence(search is trapped in a region not containing the global optimum).Selective pressure and diversity are inversely related. We replace an individual in the population with worse values for these two feature. Steady state replacement also increase the efficiency of GA because of higher selection pressure and changes in the exploration and exploitation balance caused by using different parent selection and replacement strategies.[6]

III. Conclusion

In this paper, various replacement schemes have been discussed. Elitist replacement schemes improve the performance of genetic algorithm. Using different replacement and selectionschemes in steady state genetics converge quickly and have a useful diversity. Strategies which involve conservative approach (Similar to replace random if better (RRB), replace most similar if better (RMSB), ROB)improve the performance of their pure form. However, Elitism is not directly enforced; the best individual is preserved if it is.

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