Dynamic Diversity Control in Genetic Algorithm for Extended Exploration of Solution Space in Multi-Objective TSP

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Abstract

Premature convergence in the process of genetic algorithm (GA) for searching solution is frequently faced and the evolutionary processes are often trapped in a local but not global optimum. This phenomenon occurs when the population of a genetic algorithm reaches a suboptimal state that the genetic operators can no longer produce offspring with a better performance than their parents. In the literature, plenty of work has been investigated to introduce new methods and operators in order to overcome this essential problem of genetic algorithms. As these methods and the belonging operators are rather problem specific in general.

In this research, we observe the progress of the evolutionary process, and when the diversity of the population dropping below a threshold level then artificial chromosomes with high diversity will be introduced to increase the average diversity level thus to ensure the process can jump out the local optimum. The proposed approach is implemented independently of the problem characteristics and can be applied to improve the global convergence behavior of genetic algorithms. We eventually apply this approach to solve Multi-Objective (MO) Traveling Salesman Problem (TSP) which were combined KroA with KroB, KroC, KroD and KroE to be trade-off problems. The result shows the solution quality to validate the adaptability of DDCGA for solving such problems.

1. Introduction

The fundamental principles of GAs were first presented by Holland [1]. Since that time, GAs have been successfully applied to a wide range of problems. An overview of GAs and their implementation in various fields is given by Goldberg [2] or Michalewicz [3]. As Ursem [4] pointed out, the diversity measure is traditionally used to analyze the evolutionary algorithms rather than guide them. However, a new application by adaptive controlling; that measuring and using different properties of the swarm / population while running, adds significant potential to the algorithm.

In this research, we have therefore adopted the idea from Ursem [4] with the decreasing and increasing diversity operators to control the population diversity. Therefore, the control mechanism is built into the GA, and the idea is to control the diversity of the population by injecting Diversified Artificial Chromosomes (DAC) into the system until the diversity measure reaches a certain level than stop. In this research, for verifying the feasibility of this idea, the TSP is applied to develop the theory; moreover, the parameters will be revised through design of experiments (DOE) of TSP, eventually, we will apply the philosophy to solve the simulated multi-objective problems by way of combining several problems in TSPLIB.

2. Traveling salesman problems

The TSP objective is to find the shortest route for a traveling salesman who, starting from his home city, has to visit every city on a given list precisely once and then return to his home city. The main difficulty of this problem is the immense number of possible tours; this is a problem in discrete or combinatorial optimization. It is a prominent illustration of a class of problems in computational complexity theory which are classified as NP-hard. Therefore, we apply TSP to do the feasibility study which is applied to solve the multi-objective problems, which has high similarity with production scheduling problems. In the problems of combining several TSP instances, we assume one instance is to search the shortest route; the other is to find the lowest cost. As we realize the problems of the property of trade-off, we apply two instances to be the two objectives of fitness to search the Pareto solutions.

3. Multi-objective optimization

Chang [6] concluded, for converting multi-objective optimization problem of the Pareto front (PF) into a number of scalar optimization problems.

The set of all the optimal Pareto solutions in the objective space is called the PF. The most popular one among them is the weighted sum approach proposed by Miettinen [6] which is introduced in the following:

The approach considers a convex combination of the different objectives.

Let $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_m)^T$ be a weight vector, i.e., $\lambda_i \geq 0$ for all $i = 1, \ldots, m$ and $\sum_{i=1}^{m} \lambda_i = 1$. Then, the optimal solution to the following scalar optimization:

$$\text{Minimize } g^{ws}(x \mid \lambda) = \sum_{i=1}^{m} \lambda_i f_i \tag{1}$$

Subject to $x \in \Omega$

is a Pareto optimal point to (1), where we use $g^{ws}(x \mid \lambda)$ to emphasize that λ is a coefficient vector in this objective function, while x is the variables to be optimized. To generate a set of different Pareto optimal vectors, one can use different weight vectors x in the above scalar optimization problem. If PF is convex, this approach would work well. Hence, we apply the approach of weighted sum in this research to solve bi-criterion TSP. Base on the weighted summation; we define the objective function which is the fitness in the DDCGA as the following formula:

$$fitness = \alpha \cdot KroA + (1-\alpha) \cdot Kro(B, \ldots, E) \tag{2}$$

Where

$\alpha = 0, 0.1, \ldots, 1$, which is the weight of KroA. $(1-\alpha)$ is the weight of others

4. GA with dynamic diversity control

The architecture of a Dynamic Diversity Control Genetic Algorithm (DDCGA) is shown in Figure 1. Once the diversity of the population reaches to the threshold, the system will introduce a certain level of artificial chromosomes with high diversity into the mating pool. As observed phenomenon during the evolutionary process, when the fitness reaches to a local optimum, the chromosomes within the last couples of population will be very homogenous. Thus, the genetic operators cannot further generate good chromosomes to jump out the local optimality.

In order to generate artificial chromosomes with high diversity, we need to breed a set of seed chromosomes before hand and these seed chromosomes are retrieved from the earlier evolutionary process. The artificial chromosomes are generated from the set of breeding pool when the diversity of the population reaches a low threshold value. These artificial chromosomes are injected into the evolutionary process and the genetic operators will be able to generate new generations hopefully will lead the process to jump out the local traps.

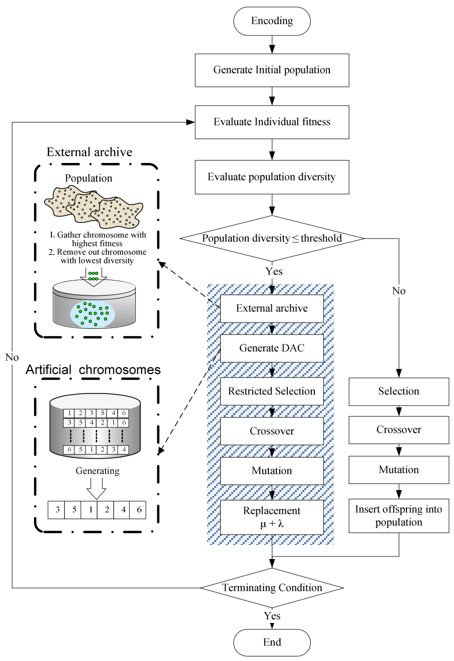

Fig. 1. The Architecture of DDCGA

Consequently, DAC is integrated into the procedure of Genetic Algorithm and it attends to improve the diversity performance of Genetic Algorithm, the pseudo code of the DDCGA algorithm which is listed as follows:

```
Population: The population used in the GA
Generations: The number of generations
Termination Condition:

Initialize Population
while termination condition is not satisfied do
    Evaluate fitness and diversity of population
        if population diversity > threshold then
            Selection operator
            Crossover operator
            Mutation operator
        else
            Create artificial chromosomes
            Select parents and artificial chromosomes applied by Selection operator
            Crossover operator
            Mutation operator
        μ + λ Replacement
    end if
end while
```

The primary procedure is to collect gene information first from the external archive and to use the gene information to generate artificial chromosomes. Before collecting the gene information, AC collects the chromosomes whose fitness is better by comparing the fitness value of each chromosome with average fitness value of current population. Thus, the average fitness is calculated.

There are totally two phases in the process of DDCGA; one is SGA, when population diversity is larger than threshold, another phase is DAC to enhance the population diversity through inject artificial chromosomes into the mating pool.

5. Diversity measure

We have discussed about the major problem in traditional GAs. The applied approach to measure diversity between chromosomes and injection timing is extremely important to overcome this kind of premature problems.

The DGEA applies diversity-decreasing operators (selection and recombination) as long as the diversity is above a certain threshold d_{low}. When the diversity drops below d_{low}, the DGEA switches to diversity-increasing operators (mutation) until a diversity of d_{high} is reached. Hence, phases with exploration and phases with exploitation will occur. Theoretically, the DGEA should be able to escape local optima because the operators will force higher diversity regardless of fitness.

If $d_{low} = d_{high,}$ the algorithm will maintain a diversity close to the given threshold value, which is particularly useful for dynamic and multi-objective optimization tasks.

Diversity measures are highly problems depended, in different kinds of combination problems, we need to find some methodologies to measure the individual diversity between the best fitness and individual chromosome, denotes X. Others chromosomes denote set $\boldsymbol{Y}$ and L is the length of a chromosome.

The published research proposed five kinds of individual diversity measure approaches which are listed as follow:

Hamming distance:

$$D(X,Y) = \sum_{i=0}^{L} (x_i - y_i) \tag{3}$$

6. Experimental results

In order to test the effectiveness of the diversity threshold control mechanism, a set of experimental tests are conducted. In these experiments, three instances were chosen for TSPLIB library and computed by SGA and DGA. DGA use information entropy to measure diversity and calculate population diversity by Arithmetic average. Diversity threshold was set by 0.1 form previous tests. All of instances executed thirty times. We discover that when the entropy decreases, the diversity also decreases simultaneously, which can be observed in Figure 2.

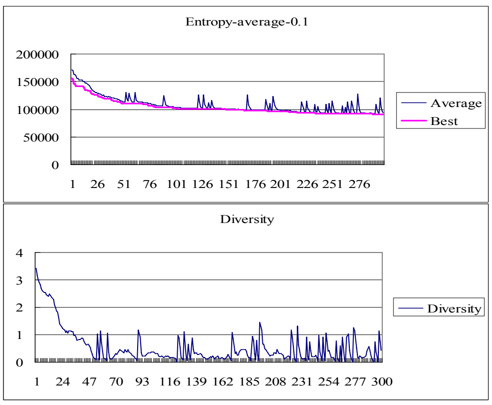

Fig. 2. The population diversity enhance occasion.

From the tests of parameters in TSP by empirical experiment design, we found the average fitness of DGA is much closer to the best optimal. The comparisons results of SGA and DGA are shown in Table 1. are satisfactory. Beside, the variance of DGA is smaller than SGA's, therefore, we ensure that inject diversity to traditional GAs will help effectively escape local optimal. Base on the above experiments of the philosophy of DDCGA, we could try to apply the idea to solve multi-objective problems; hence, we further do several experiments, which are listed as Table 2.

TABLE 1
COMPARISONS OF SGA WITH DGA IN TSP INSTANCES

	Instance	KroA100	KroA150	KroA200
SGA	Average	37252.933	49733.867	62336.570
	STD	3055.922	2791.933	3746.182
DGA	Average	33511.130	43053.240	57616.457
	STD	2886.743	2316.039	3712.752
Improvement	%	10.04%	13.43%	7.57%

In this research, there are total five instances applied to objectives. We assume KroA is the classic traveling salesman problem; the others are regarded as the cost problems.

TABLE 2
APPLYING DDCGA FOR SEARCHING THE PARETO FRONT SOLUTIONS IN MOTSP

(α)	KroA (α)	KroB (1-α)	KroA (α)	KroC (1-α)	KroA (α)	KroD (1-α)	KroA (α)	KroE (1-α)
0.0	173472	73918	171806	74735	167276	74049	171724	77657
0.1	144616	75622	149175	76180	143243	75712	144338	79495
0.2	130171	79292	128669	81194	128881	80005	127514	83202
0.3	116521	84706	118166	85487	113812	85002	115827	89744
0.4	107907	91215	107244	91185	107090	90337	105901	94834
0.5	99135	97706	99887	99043	97983	96328	98697	100988
0.6	92455	105035	93125	107255	91124	106047	91510	110118
0.7	84888	119349	86711	116792	86184	115904	85341	117655
0.8	81312	129174	81196	129976	81989	126146	80237	130591
0.9	76727	146499	78148	147255	77354	141101	77476	149100
1.0	76726	169420	74852	172730	75956	163956	76722	171706

From the data we obtain in this experiment shown in Table 2, the Pareto solutions are plotted respectively in Figure 3. The illustrations plotted are KroAB100, KroAC100, KroAD100 and KroAE100, these all represent multi-objective feasible solution sets.

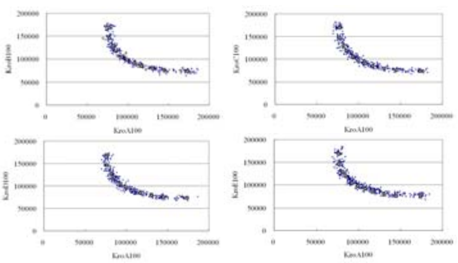

Fig. 3. Pareto solution by DDCGA for Combinatorial TSP

7. Conclusion

Although these results are not satisfactory for searching Pareto front solution in multi-objective problems, these experiments revealed several interesting features of the DDCGA. First, the DDCGA outperformed the other algorithms by significant percentages on all single objective test problems. Second, the control mechanism by injecting artificial chromosomes with high diversity is very effective, the diversity of the population increased significantly after introducing these artificial chromosomes. The mechanism will re-inject the diversity for decreasing to the minimum threshold value. However, the results showed some variation in the reduction percentages, which indicates that this could be problem dependent.

As these experiments, if the external archive is to retrieve the chromosomes with higher diversity, and then mining these chromosomes to generate artificial chromosomes to be injected into the evolutionary process. In this research, this control mechanism can simultaneously keep the characteristics of exploration and exploitation which also explain why we apply the philosophy for multi-objective problems; we will further do more experiments for obtaining more satisfactory fitness.

10. References

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