Genetic Fuzzy Rules for DOPs

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ABSTRACT

Dynamic Optimization Problems (DOPs) are a defiance for Genetic Algorithms. In DOPs, a varied number of optima, either local or global, that dynamically change their position and shape in the search space. When applied to DOPs, the standard Genetic Algorithms (SGAs) loose the population diversity. This diversity is necessary for locating multiple optima and for adapting to changes in them. Many researchers have proposed algorithms to enhance the performance of GAs in DOPs. This paper is motivated for applying multi-modal optimization technique with a number of remedies to address dynamic optimization problems. First, we use GAs with Dynamic Niche Sharing (GADNS) to maintain diversity in population and to find multiple optima. Second, we perform with an unsupervised fuzzy clustering algorithms to track multiple optima and to overcome some limitations of GADNS. Third, we use a fuzzy system to adjust the population diversity with the mutation and crossover rates. A novel genetic operator inspired by bacterial conjugation is used to improve GAs. A modified tournament selection is used to control the selection pressure. The effectiveness of our approach is demonstrated by using Generalized dynamic benchmark generator (GDBG).

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem solving—*Heuristic Methods, Scheduling*

General Terms

Algorithms

Keywords

Genetic Algorithms, Unsupervised Learning, Fuzzy Clustering, Dynamic Optimization.

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G2ECCO'12 Companion, July 7–11, 2012, Philadelphia, PA, USA.
ACM 978-1-4503-1178-6/12/07.

1. INTRODUCTION

In recent years, there has been a growing motivation for tackling DOPs, this is due to its wide applications in the real world. When applying Genetic Algorithms (GAS) in DOPs, the aim is to improve GAs that can track the moving optima with time. Once Converged, GAs loose diversity and cannot adapt well to the changing environment.

This paper presents an iterative technique based on Genetic Algorithms with Dynamic Niche Sharing, in order to maintain the diversity of the population. The platform of our iterative technique, referred by (FRDOP), is built on three components. The first is a Genetic algorithms with Dynamic Niche Sharing (GADNS), the second is an Unsupervised fuzzy clustering and the third is a Spatial separation (SS). To avoid getting stuck at a local optima, GADNS method is used to preserve genetic diversity, to encourage speciation and to form niches. But GADNS suffers from some limitations. Therefore, the second component is used to address the limitations of GADNS. SS, is the third component in FRDOP, affects each individual to its corresponding cluster. To maintain the balance between exploration and exploitation, FRDOP introduced some remedies. First, we focus to adaptively adjust mutation and crossover rates with fuzzy rules. The fuzzy system is based on considering Hill's Diversity Index and off-line error normalized. Second, the fertilization operator is proposed. The principle of this operator is to add new individuals in current population. These new individuals are the prototypes of cluster given by unsupervised fuzzy clustering algorithm. Then, we apply mutation and restricted crossover for only those prototypes. This new subpopulation is added to the current population with elitism replacement. Third, a modified tournament selection [3], is used to dynamically adjust the selection pressure.

2. SUMMARY OF THE WORK

The aim is to determine different optima of a dynamic multi-modal optimization using GADNS, the number of peaks q and characteristics corresponding niches (center, radius, cardinal, etc.). The idea is to apply an unsupervised fuzzy clustering [1] (UFL-FCM-VAL) at population of solutions produced by GADNS, in order to detect the presence of classes homogeneous and well separated. If the entropy of the fuzzy c-partition obtained is higher than ($>10^{-3}$), these solutions will be again evolved by GADNS and classified by UFL-FCM-VAL.

FRDOP is an iterative technique based on a three components. The first, is a GA which combines dynamic niche sharing and mating restriction to maintain diversity and to encourage speciation. The Second component (UFL-FCM-VAL) is based on an unsupervised fuzzy clustering algorithm, which performs the partition of the individuals given by the first component into a set of C clusters so that each of them corresponds to a niche. In addition, this component provides some important features, such as the prototypes which are the expected optima and the cluster radius which is also the niche radius. The last component (SS) implements the principle of spatial separation to generate subpopulations from the resulting cluster characteristics (center, radius). Hence, individuals undergo a cyclic process again throughout the three components of the system.
The main component of FRDOP is GADNS with three improvements. The first one, a Modified Tournament Selection (MTS) which is based on standard tournament selection. But MTS guards in each iteration the best individual. The tournament size is the number of clusters given by UFL-FCM-VAL. This tournament size control better the selection pressure [3]. The second one, the fertilization operator which allows to insert new individuals in the population. The first individuals in this sub population are the prototypes F(t), we evolved the individuals by respecting the following steps:

- apply Bacterial conjugation, Let I_f is Donor from F(t), I_m is Recipient randomly selected alternately from different population classes , the offspring is:
  C_1=0.5[(1+ρ)*I_f+(1-ρ)*I_m]
  Where ρ= exp(-zu) IF u $\in$[0,0.5]
  ELSE ρ= exp(zu),
  and u,z are random numbers between 0 and 1.
  The result is the sub population $\acute{F}(t)$;

- apply Gaussian mutation (the result is the sub population $\ddot{F}(t)$);

Each individual in {F(t)U $\acute{F}(t)$U $\ddot{F}(t)$} replaces the nearest individual in the population P(t) if it has a higher fitness. The third one represent the Fuzzy Rules for adapting mutation and crossover rates. The strategy is based on individual distribution during the evolution of the GAs. This distribution is resolved by the clustering algorithm UFL-FCM-VAL. The clustering analysis of GAs evolution in DOPs depicts four optimization state, including diversified states, before converged state, converged state, changed environment state.
Adjustments of p_x and p_m are based on considering two parameters α and β' :

The first, α=1-Hill diversity, its formula is as follows:

$$\alpha = 1 - Hill = 1 - \frac{(\frac{1}{\lambda})}{exp(H)} \quad (1)$$

$$\lambda = \sum_{i=1}^{c} \frac{N_i(N_i-1)}{N(N-1)} \quad (2)$$

$$H = -\sum_{i=1}^{c}((\frac{N_i}{N}) * Log_2(\frac{N_i}{N})) \quad (3)$$

Table 1: Heuristic Strategy of adapting P_x&P_m

		β *Value*	
		Small	Large
α Value	Large	p_x decrease p_m increase	p_x increase p_m decrease
	Small	p_x increase p_m increase	p_x increase p_m decrease

Where λ is Simpson's index, H is Shannon-Weaver's index, C is number of clusters given by UFL-FCM-VAL, N_i : Cardinal of each cluster and N is the Population Size.

The second is β'=1-Off-line error normalized
The off-line error is defined as the average of the best solutions at each time step:

$$\beta = \frac{1}{T}\sum_{t=1}^{T}(O_t - B_t) \quad (4)$$

Where B_t is the best solution obtained by an algorithm just before the environmental change, O_t is the optimum value of the environment at time t, β is the average of all differences between O_t and B_t over the environmental changes. Whereas, off-line error normalized is calculated as:

$$\beta' = 1 - \frac{1}{T}\sum_{t=1}^{T} abs(\frac{O_t - B_t}{max(O_t, B_t)}) \quad (5)$$

Hill's diversity gives the idea about the diversity of population, while off-line error normalized evaluates the performance of the approach. Table 1 summarizes the heuristic guidelines used to produce the fuzzy rules.
The performance of FRDOP is tested on six problems generated by the benchmark proposed by Li et al [4] and is compared with SGA, Random Immigrants Genetic Algorithms (RIGA) with the total number of immigrants N_i=30 and also with HyperMutation Genetic Algorithm (HMGA).
The overall performance of FRDOP is 60 %, RIGA is 49.55, HMGA is 39.11%, by against the overall performance of SGA is only 34.27%. Looking through the difficulty of the problems starting from the simplest,the small step, and through the most complicated test to optimize, SGA, RIGA and RIGA have a difficulty to optimize the problems, especially chaotic change and dimensional change. But, in all tests, FRDOP performs much better than SGA, RIGA and HMGA.

3. REFERENCES

[1] A. Bouroumi, and A. Essaïdi, Unsupervised "fuzzy learning and cluster seeking",*Intelligent Data Analysis* **4(3)**, 241–253 (2000).

[2] J. Branke, "Evolutionary Optimization in Dynamic Environments", *Kluwer Academic Publishers*, (2001).

[3] K. Jebari, A. Bouroumi, A. Ettouhami, et al, "Unsupervised fuzzy tournament selection", *Applied Mathematical Sciences*, **58**, 2863–2881 (2011).

[4] C. Li and S. Yang, "A generalized approach to construct benchmark problems for dynamic optimization", *Proceedings of the 7th Int. Conf. on Simulated Evolution and Learning, Springer*,(2008).