REALISATION OF FUZZY-ADAPTIVE GENETIC ALGORITHMS IN A MATLAB ENVIRONMENT

R. Matoušek
Institute of Automation and Computer Science
Brno University of Technology
Technická 2
616 69 Brno, Czech Republic
Email: matousek@uai.fme.vutbr.cz

Abstract
This paper discusses design of adaptive Genetic Algorithms (GA) on the base Fuzzy Inference System (FIS). There are two possible ways for integrating Fuzzy Logic and Genetic Algorithms. One involves the applications of Genetic Algorithms for solving optimization and search problem related with fuzzy systems. The another, the use of "fuzzy tools" for modeling and adapting Genetic Algorithm control parameters, with the goal of improving performance. The Genetic Algorithms resulting from this integration we called Genetic Algorithms with the Fuzzy Inference System (GA-FIS)
Keywords: genetic algorithms, fuzzy inference system, MatLab, adaptive genetic algorithms and characteristics of genetic algorithms.

1 Introduction

Applications of genetic algorithms for optimization problems are widely known as well as their advantages and disadvantages in comparison with classical numerical methods. The genetic algorithms behavior is determined by the exploration and exploitation relationship kept throughout the GA run. This balance between the utilization of the whole solution space and the detailed searching of some parts can be adapted to change of GA operators setting (i.e. selection, crossover and mutation). Fuzzy logic controllers may be used for dynamically computing appropriate GA control parameters using the experience and knowledge of the GA experts. This adaptive change of the selected GA parameters is making by way of Fuzzy Inference System on the base GA feedback [1,2,3]. GA feedback is realized by means of special designed GA characteristics. The FIS is designed on the base GA expert knowledge.

2 Classification of Control Techniques

In classifying parameter control techniques of a genetic algorithm, many aspects can be taken into account [Eiben, Á.E., Michalewicz, Z., et al.]. For example:

- *What is changed*? (e.g., representation, evaluation function, setting of GA operators)
- *How the change is made*? (i.e., deterministic heuristic, feedback-based heuristic, etc.)
- *The scope/level of change*. (e.g. population-level, individual-level, etc.)

This terminology can be leads to the taxonomy illustrated in Figure 1.

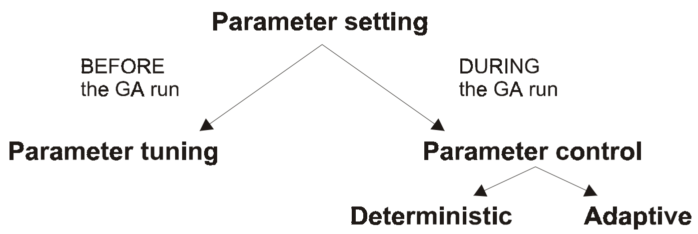

Fig. 1: Taxonomy of parameter setting

Deterministic parameter control: This takes place when the value of strategy parameter is altered by some deterministic rule. This rule modifies the strategy parameter deterministically without using any feedback from the search process. Usually, a time varying schedule is used, i.e., the rule will be depended on the number of actual generation (iteration), e.g. [4].
Adaptive parameter control: This takes place when there is some form of feedback from the state of GA population and/or the search (optimization) process that is used to determine the direction and magnitude of the change to the strategy GA parameter.

3 Optimization and Simple GA

The optimization task by GA is assumed to be

$$\max\left\{F(\mathbf{a})\,|\,\mathbf{a}\in\{0,1\}^l\right\}, \tag{1}$$

$$\min\left\{f(\mathbf{a})\,|\,\mathbf{a}\in\{0,1\}^l\right\}, \tag{2}$$

where F is objective function denoted as fitness function – satisfies $F(\mathbf{a})>0$, $\forall\mathbf{a}$. For next discussion we will assume minimization optimization task with objective function $f(\mathbf{a})$ by (2). The current simple GA consists of n binary strings $\mathbf{a}$ (individual), each of them of length l. This set of n individuals is denoted as population $\mathbf{P}$. Each individual $\mathbf{a}$ is a feasible solution to problem (2). The transition between successive populations ($\mathbf{P}_i$,$\mathbf{P}_{i+1}$,…) is achieved by applying the genetic operators of *selection S*, *crossover C* and *mutation M*. This transition is denoted as a *generation* (in numerical terminology as an iteration). The simple GA with a generation model was used [5,7]. The short formal description of the GA is:

$$\mathbf{P}_{i+1}=g(\mathbf{P}_i,\xi),\;\;\xi\in(S,C,M)\,, \tag{3}$$

where $\mathbf{P}_o\equiv$ pseudo-random or heuristic setting. As we know, selection, crossover and mutation operators determine genetic algorithm's behavior. Selection operator has influence on the convergence behavior of GA. The high-level selection pressure evokes premature convergence and low-level one evokes long convergence time of GA. The crossover facilitates the exploration, while the mutation facilitates the exploitation of the space.

4 Design of GA-FIS

Fuzzy Inference System is used for the control of GA parameters. The following must be determined for applications of FIS to control the GA parameters:

- Input values
  The input values are crisp numbers. This inputs are obtain from special GA characteristics as you can see in next Section 4.2.
- Model of FIS with crisp output
  The fuzzy inference system is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The crisp outputs represents parameters of GA operators. Outputs are obtained by means of defuzzification.

With crisp inputs and outputs, a fuzzy inference system implements a nonlinear mapping from its input space to output space:

$$output=h_{FIS}(input)\,. \tag{4}$$

4.1 Genetic Algorithms with Fuzzy Inference System

Genetic Algorithm with the Fuzzy Inference System is a Genetic Algorithm (3) with adaptive setting (absolutely or relatively) of GA parameters (FIS *outputs*) on the base special GA characteristics (FIS *inputs*). A Design of GA-FIS was limited to setting strategy GA operators, such as selection and mutation rate (and crossover rate) during the GA run. The fuzzy control action is applied if the condition of fuzzy adaptation is true.

The arguments why not to use the fuzzy control during the complete run of GA are as follows:

1. The time cost of calculating of FIS must be respected.
   Note: This argument can be eliminated if we used suitable mapping function for conversion a single FIS to some LookUpTable matrixes.

$$output = h_{LookUpTable}(input)\ . \tag{5}$$

2. After changing the value of GA parameters it is reasonable to let some time-generations for stabilization of GA process.
3. If convergence of GA is acceptable it is not possible to use fuzzy control action.

These three arguments represent *"Condition of Fuzzy Adaptation"* in our algorithm given by Figure 2.

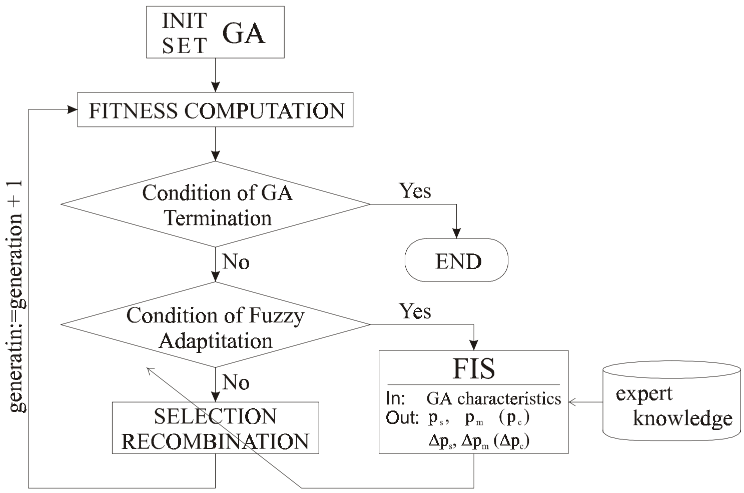

Fig. 2: The principle of GA-FIS

4.2 Special GA characteristics

The input values (4) are extracted from quantitative characteristic of GA. Various types of these characteristics and suggestions are contained e.g. in [1,2,3,5,6]. For our researching we categorized the GA characteristic in relation to GA population **P** or search (optimizing) process by means of objective function values (2) $z = f(\mathbf{a})$.

- q_{varHD} coefficient of measure utilization of Hamming spaces is a characteristic of a binary represented population **P**.
  Let us have n individuals, each individual is binary string $\mathbf{a} \in \{0,1\}^l$. It is possible to define the population **P**, Hamming metric ρ_H and matrix of Hamming distances $\boldsymbol{\rho}_H(\mathbf{P})$:

$$\mathbf{P} = \left(a_{i,j}\right)_{\substack{i\in\{1,2,\ldots n\}\\ j\in\{1,2,\ldots l\}}} = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,l} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,l} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \cdots & a_{n,l} \end{pmatrix}, \tag{6}$$

$$\rho_H(\mathbf{a},\mathbf{b}) = \sum_{j=1}^{l} \left|a_j - b_j\right|,\ \ \rho_H \in \mathbb{N}\,, \tag{7}$$

Further the sum of Hamming distances:

$$HD_{sum}(\mathbf{P}) = \sum_{i=1}^{n}\sum_{i=1}^{n}\rho(\mathbf{a_i},\mathbf{a_i}) \,, \tag{8}$$

and HD_{max} (10) as solution of equation (9) for our case of GA:

$$HD_{\max}(n,l) = \max\left\{HD_{sum}(\mathbf{P}) \mid \mathbf{P} \in \{0,1\}^{n\cdot l}\right\}, \tag{9}$$

$$HD_{\max}(n,l) = \begin{cases} \frac{1}{2}n^2 l & n \in \mathbb{N}_{even} \\ \frac{1}{2}(n^2-1)l & n \in \mathbb{N}_{odd} \end{cases}. \tag{10}$$

We reflect only $n \in \mathbb{N}_{even}$ for practical GA realization. From equation (8) and (9) we defined the FIS input q_{varHD}:

$$q_{varHD} = \frac{HD_{sum}}{HD_{\max}}, \;\; q_{varHD} \in [0,1] \tag{11}$$

- q_{cpc} coefficient of partial convergence. This coefficient determines the average (or weight average) change of a standard value of objective function for sample of successive populations.

$$q_{cpc} = \sum_{i=g-k+1}^{g} z_{\Delta rel,i}, \;\; q_{cpc} \in [-1,1] \tag{12}$$

$$z_{\Sigma}(g,n,k) = \sum_{i=g-k+1}^{g} \left|z_{n,i}\right| \tag{13}$$

$$\mathbf{z}_{\Delta rel}(g,n,k) = \begin{cases} \mathbf{0} & z_{\Sigma} = 0 \\ \left(\dfrac{z_{n,i+1} - z_{n,i}}{z_{\Sigma}}\right)_{i=g-k+1,\dots,g-1,g} & z_{\Sigma} \neq 0 \end{cases} \tag{14}$$

Where: g…generation index, k…size of sample $g \geq k \geq 2$

n…fitness index z…objective function value $z_{g,n} \leq z_{g,n+1}$

Further characteristic [1,2,3] where we trying can by used:

- q_{varBC} variability of population,
- H^1, H^2 set of H-characteristics based on statistical analyses of objective function,
- etc.

4.3 Fuzzy Inference System

Fuzzy inference systems are the most important modeling tool based on fuzzy set theory. Our fuzzy FIS is build by domain experts [3,5,8,9] and is used for automatic adaptation (control) of strategy GA parameters (see Fig. 2).

Example of two-input single output fuzzy model where we used in our experiments is in Figure 3.

The MatLab® Fuzzy Logic Toolbox was use for FIS development. A short description of FIS:

- INPUT: GA characteristics (q_{varHD}, q_{cpc}, can be use other)
- FUZZY MODELS:
    - The Mandani fuzzy inference system using *min* and *max* for T-norm and T-conorm operators, respectively.
    - The Sugeno (TSK)fuzzy model.
- FUZZY RULES and MEMBERSHIP FUNCTION: build by domain expert knowledge
- OUTPUT: crisp values of selected GA parameters (we have to use a defuzzifier to convert a fuzzy set to a crisp value).
    - Absolute values of selected GA parameters e.g.:
        - p_s … selection (power of tournament)
        - p_m … mutation (percentage of bit mutation).
    - Relative values of selected GA parameters e.g.: Δp_s, and Δp_m.

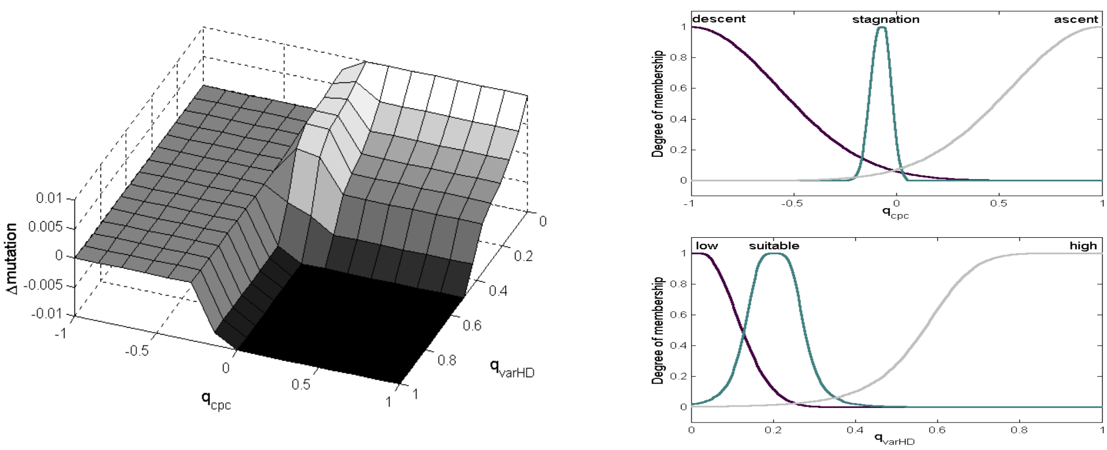

Fig. 3: An example of antecedent membership functions and overall input-output surface for relative setting of the mutation operator.

5 Test Problem

For the testing of the performance of evolutionary heuristic algorithms, such as GA, some set of artificial designed optimization problems was used. The test function denoted as Rastigrin's function - F6 in static and dynamic variant was used. Dynamic variant of a F6 is own modification. The random shift vector for modification of **x** vector is used. Trajectory of global optimum for tested variant of dynamic F6 is shown in Figure 4.

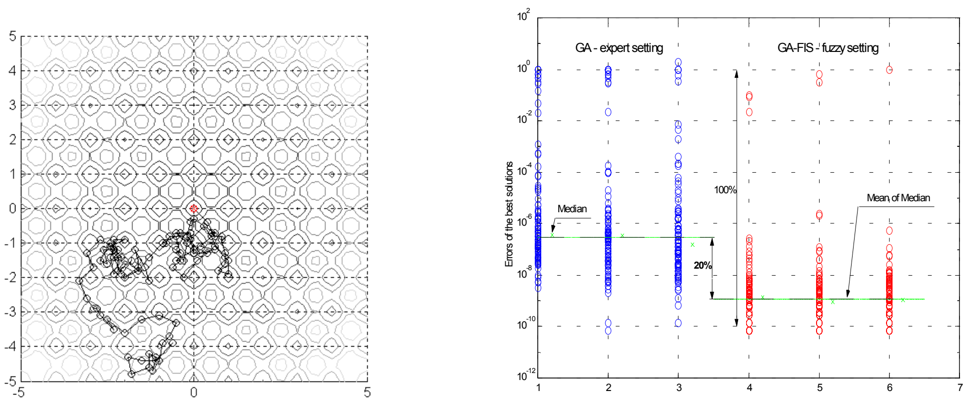

Fig. 4: Rastigrin's function – a dynamic location of minimum and Statistical compassion of the quality of solutions for given GA algorithms

6 Conclusion

Applications of fuzzy methods in the area of GA (and generally even EA) is already producing and will continue to produce interesting results, in the same way as application of GA produced good results in the area of fuzzy regulators design. Areas for application of "fuzzy tools" are rather diverse:

- Fuzzy adaptation of genetic operators using FIS and GA feedback
- Fuzzy adaptation of other strategic GA parameters as population size
- Fuzzy genetic operators, etc.

These areas were, are and will be discussed by many researchers [9,10,11] and the others. Our study of given class of problems showed positive influence of fuzzy adaptation to solutions of static and dynamic optimization problems. Better results of GA-FIS in compare with GA for this class of test problems are definitely statistically proved. Quantitatively it is about 10-20% improvement to classic GA performance. This evaluation even includes computational complexity of FIS. The computational complexity was in practical realization reduced by using: constraints of fuzzy adaptation and convenient projection of FIS into several LookUpTable matrixes.

Generalization of these results to other optimization problems is of course debatable. It is necessary to keep in mind that following will probably always be true in optimization:

"Particular optimization method is as universal as the class of problems it solves is limited."

However some optimism is appropriate based on other unpublished tests. GA-FIS design was based on expert knowledge of many authors about GA behavior. So this mechanism is much more user-friendly tool than classic GA, where all GA operator parameters had to be adjusted manually. Concrete ways to further improvement of GA-FIS are in:

1. Models of FIS of better quality or more purpose-oriented.
2. Understanding of GA behavior and resulting proposals of new GA characteristics.

Generalization of results and methods leading to higher performance of fuzzy adaptive GA-FIS will be subjects of further research.

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