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ADAPTIVE GENETIC FUZZY SYSTEMS IN INDUSTRY: CURRENT FRAMEWORK AND NEW TRENDS

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Abstract:
Adaptive genetic fuzzy systems are ability to solve different kinds of problems in various application domains. There is an increasing interest to mix fuzzy systems with learning and adaptation capabilities. Adaptive genetic fuzzy systems are very hybridizing the approximate reasoning method of fuzzy systems with the adaptive and evolutionary algorithms. Learning/optimization methods drawn from both fuzzy theory and genetic algorithms are used to find the optimal strategy.
This paper provide an account of genetic fuzzy systems, with special attention to adaptive genetic fuzzy rule-based systems. After a brief introduction to models and applications of genetic fuzzy systems, critical evaluation is elaborated. The resulting expert system is an open system that uses frames, rules, fuzzy implication and connection matrices to produce a form of machine learning. Authors open questions for the future investigation of new trends in genetic fuzzy systems.

Keywords:
Fuzzy, Expert System, Genetic Algorithm

1. INTRODUCTION

Fuzzy systems successfully purposed to problems in classification [1.], modeling [2.] control [3.], in industry applications. The key for success was the ability of fuzzy systems to incorporate human expert knowledge.

One of the most approaches have been the hybridization attempts made in the framework of soft computing, were different techniques, such as neural and evolutionary, provide fuzzy systems with learning capabilities, as shown in Figure. 1. Neuro-fuzzy systems are one of the most successful and visible directions of that effort [4.,5.,6.]. A different approach to hybridization leads to genetic fuzzy systems (GFSs) [7.].

A GFS is basically a fuzzy system augmented by a learning process based on a genetic algorithm (GA). GAs are search algorithms, based on natural genetics, that provide robust search capabilities in complex spaces, and thereby offer a valid approach to problems requiring efficient and effective search processes [8.].

Genetic learning processes cover different levels of complexity according to the structural changes produced by the algorithm [9.], from the simplest case of parameter optimization to the highest level of complexity of learning the rule set of a rule based system. Parameter optimization has been the approach utilized to adapt a wide range of different fuzzy systems, as in genetic fuzzy clustering or genetic neuro-fuzzy systems.

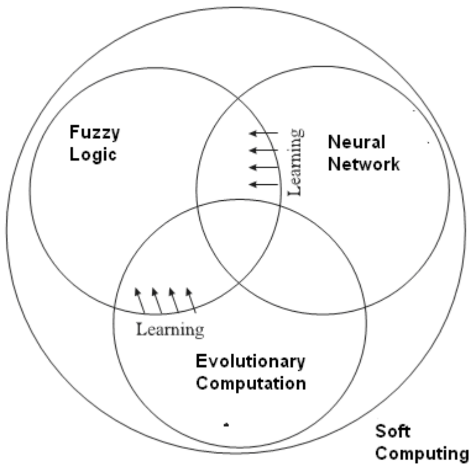

Figure 1 soft computing and learning in fuzzy system

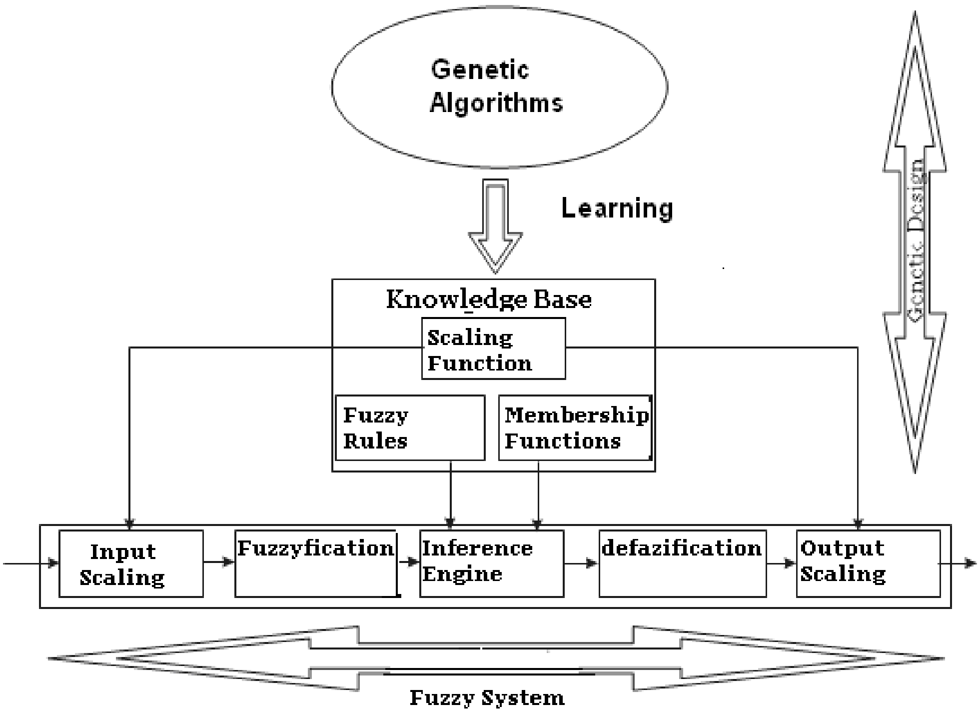

Figure. 2. Genetic design and fuzzy processing

Analysis of the literature shows that the most prominent types of GFSs are genetic fuzzy rule-based systems (GFRBSs) [10.], whose genetic process learns or tunes different components of a fuzzy rule-based system (FRBS). Figure. 2 shows this conception of a system where genetic design and fuzzy processing are the two fundamental constituents. Inside GFRBSs it is possible to distinguish between either parameter optimization or rule generation processes, that is, adaptation and learning.

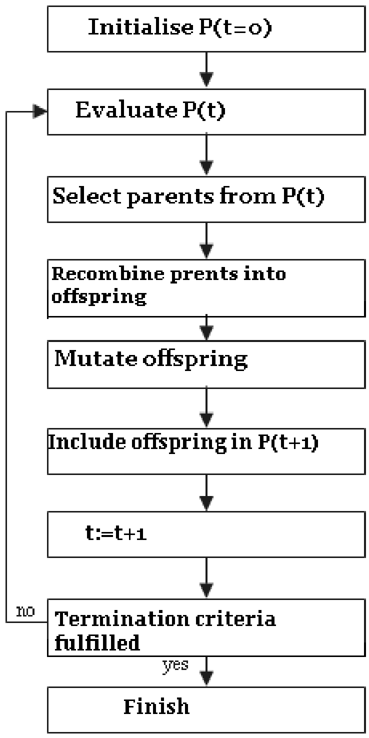

Figure. 3. Principal structure of a genetic algorithm

2. GENETIC ALGORITHMS

GAs are general purpose search algorithms which use principles inspired by natural genetics to evolve solutions to problems [8.]. The basic idea is to maintain population of chromosomes (representing candidate solutions to the concrete problem being solved) that evolves over time through a process of competition and controlled variation.

A GA starts with a population of randomly generated chromosomes, and advances towards better chromosomes by applying genetic operators modeled on the genetic processes occurring in nature. The population undergoes evolution in a form of natural selection.

During successive iterations, called generations, chromosomes in the population are rated for their adaptation as solutions, and on the basis of these evaluations, a new population of chromosomes is formed using a selection mechanism and specific genetic operators such as crossover and mutation. An evaluation or fitness function must be devised for each problem to be solved.

Given a particular chromosome, a possible solution, the fitness function returns a single numerical value, which is supposed to be proportional to the utility or adaptation of the solution represented by that chromosome.

Although there are many possible variants of the basic GA, the fundamental underlying mechanism consists of three operations: evaluation of individual fitness, formation of a gene pool (intermediate population) through selection mechanism, and recombination through crossover and mutation operators. Figure 3 illustrate this operation mode. The specific characteristics of the evaluation method are quite dependent on the application.

As previously stated, genetic learning processes cover different levels of complexity, from parameter optimization to learning the rule set of a rule based system. Genetic learning processes designed for parameter optimization usually fit to the description given in previous paragraphs, but when considering the task of learning rules in a rule based system, a wider range of possibilities is open.

3. GENETIC FUZZY RULE-BASED SYSTEM

The mean point is to employ an evolutionary learning process to automate the design of the knowledge base, which can be considered as an optimization or search problem.

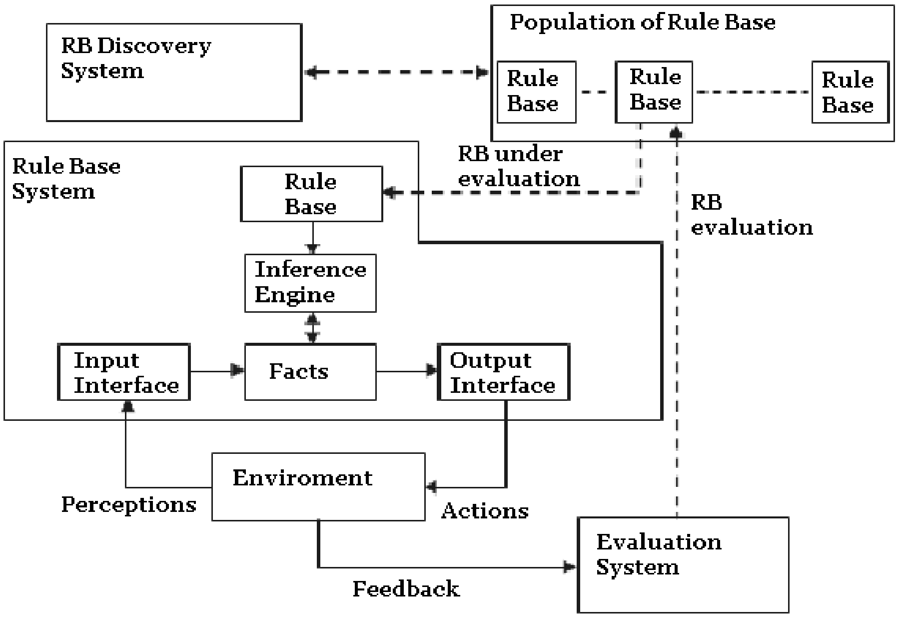

Figure. 4. Learning with the Pittsburgh approach

From the viewpoint of optimization, the task of finding an appropriate knowledge base (KB) for a particular problem, is equivalent to parameterize the fuzzy KB (rules and membership functions), and to and those parameter values that are optimal with respect to the design criteria. The KB parameters constitute the optimization space, which is transformed into a suitable genetic representation on which the search process operates.

The first step in designing a GFRBS is to decide which parts of the KB are subject to optimization by the GA. The KB of an FRBS does not constitute a homogeneous structure but is rather the union of qualitatively different components. KB of a descriptive Mamdani-type FRBS is comprised of two components:

- a data base (DB), containing the definitions of the scaling functions of the variables and the membership functions of the fuzzy sets associated with the linguistic labels, and
- a rule base (RB), constituted by the collection of fuzzy rules.

The decision on which part of the KB to adapt depends on two conflicting objectives: dimensionality and efficiency of the search.

A search space of a smaller dimension results in a faster and simpler learning process, but the obtainable solutions might be suboptimal. A larger, complete search space that comprises the entire KB and has a finer dimensionality is therefore more likely to contain optimal solutions, but the search process itself might become prohibitively inefficient and slow.

First of all, it is important to distinguish between tuning (alternatively, adaptation) and learning problems:

- Tuning is concerned with optimization of an existing FRBS, whereas learning constitutes an automated design method for fuzzy rule sets that starts from scratch.
- Learning processes perform a more elaborated search in the space of possible RBs or whole KBs and do not depend on a predefined set of rules.

Summing up, the classical genetic learning procedures to evolve FRBSs are:

- Genetic tuning of the DB,
- Genetic learning of the RB,
- Genetic learning of the KB.

Although the review is by no means exhaustive, this section reviewed the most important approaches found in the literature.

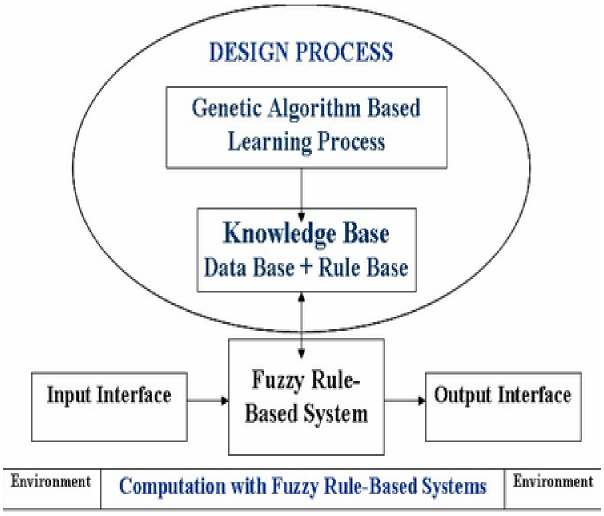

Figure 5. Genetic fuzzy systems

4. APPLICATIONS OF GENETIC FUZZY SYSTEMS

Authors provides a computational framework to address design, analysis and modeling problems in the context of uncertain and imprecise information. Its constituents fuzzy logic, neural networks, probabilistic computing and evolutionary algorithms are considered as complementary and synergistic partners rather than competing methodologies.

Neuro-fuzzy systems [5.] are by far the most prominent and visible representative of hybrid systems in terms of number of applications.

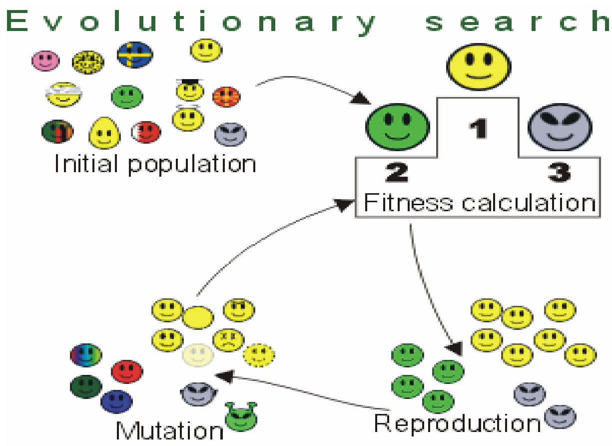

Figure 6. Evolutionary search

Compared to neuro- fuzzy systems, GFS applications until today remained less visible, in particular in an industrial setting.

In a second phase, the GA tunes the membership functions causing a local adaptation. Adaptation of membership functions for a controller with properly tuned scaling factors only results in a marginal improvement.

The role of the evolutionary algorithm is to adapt the number of rules and to fine tune the membership functions to improve the performance of fuzzy systems for estimation and control.

In [11.], Mizutani propose a hybrid neuro-genetic–fuzzy system for computerized colour prediction, a challenging problem in paint production.

Their architecture for colour paint manufacturing intelligence cannot be characterized as conventional GFSs in which the evolutionary algorithm optimizes the fuzzy knowledge base. Instead, colour expert knowledge is expressed by fuzzy rules.

Bonissone et al. apply evolutionary techniques to tune a fuzzy decision system [12.]. The fuzzy system automatically classifies the risk of an insurance application, which in turn determines the premium to be paid by the applicant.

In [14] Latinovic presents an approach to modeling genetic fuzzy real-time expert diagnostic system for PLC controlled manufacturing system in Tobacco Industry in Banjaluka. These approaches to modeling inspired by biological evolution are called evolutionary computation. It contains the design and engineering knowledge about the manufacturing system to be diagnosed.

The list of applications above indicates that GFSs can contribute to solve industrial and commercial problems. The major driving force behind this development is the need for low-cost solutions that utilize intelligent tools for information processing, design and optimization. GFSs can reduce the cost and time required to design, autonomously operate and maintain systems with a high degree of machine intelligence for control, prediction, modeling and decision making.

5. NEWTRENDS IN GENETIC FUZZY RULE-BASED SYSTEMS

In addition to the classical systems, here new directions to apply genetic (evolutionary) techniques to FRBSs are explored:

1. Genetic selection of fuzzy rule sets
2. Genetic feature selection
4. Learning knowledge bases via genetic derivation of data bases
5. Maintaining interpretability via multi-objective genetic processes
6. Genetic-based learning approaches considering different model structures
7. Genetic-based learning approaches with sophisticated genetic algorithms
8. Genetic-based machine learning approaches
9. Genetic fuzzy neural networks
10. Genetic fuzzy clustering algorithms

Until recently, there was no systematic procedure to design and develop fuzzy systems. A common approach was defining fuzzy systems based on expert knowledge and testing them to verify if the design is satisfactory. However, when expert knowledge is lacking or when considerable amount of data must be processed and analyzed, purely knowledge-based design approaches become limited.

Machine learning approaches have shown to be useful in these cases. For instance, neural networks can learn from data, but the linguistic representation of fuzzy rules and their transparency may be lost [13.].

GA-based approaches have been developed to learn:

a) membership functions with fixed fuzzy rules ,
b) fuzzy rules with fixed membership functions ,
c) fuzzy rules and membership functions using (a) and (b) in alternate steps ,
d) membership functions and RB simultaneously ,
e) Rules and RB structure and parameters (granularity, rule antecedent aggregation operator, rule semantics, rule base aggregation operator, defuzzification, membership function shape and parameters) simultaneously.

6. CONCLUSIONS

The last decade has seen a large interest in technologies that have as their motivation some aspect of human function. Some of these, like artificial intelligence, can be seen to be rooted in the psychological domain. Others, like neural networks, genetic algorithms, and evolutionary programming, are inspired by reconsiderations of biological processes.

Common to all these so-called "intelligent technologies" is a need to represent knowledge in a manner that is both faithful to the human style of processing information as well as a form amenable to computer manipulation

This paper provided an account of the current status of GFSs after many years of considerable research and development effort. In addition to a brief overview of the field to address the classical models and applications, new trends have been identified. A critical evaluation of the contribution that GFSs bring to knowledge acquisition and fuzzy rule base design was conducted, and challenges for further developments in the field were outlined. From authors point of view we need to build hybrid intelligent systems that go beyond simple combinations.

Development of GFSs that offer acceptable trade-of between interpretability and accuracy is also a major requirement for efficient and transparent knowledge extraction. Discovery of more sophisticated and new evolutionary learning models of GFSs and its application to new areas and problems still remain as key questions for the future development trends of GFSs.

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