ORIGINAL RESEARCH PAPER

Volume-7 | Issue-12 | December-2018 | PRINT ISSN No 2277 - 8179

INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH

IMPROVING FUZZY FRAMEWORK UTILIZING TRANSFORMATIVE CALCULATION

Computer Science

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ABSTRACT

Fuzzy systems have proved their capabilities to simplify numerous categories of problems comprising of different engineering domain fields. Now a-days researchers are taking keen interest towards integrating fuzzy systems with learning and adaptation capabilities. The two well known methodologies to augment fuzzy systems along with learning and adaptation procedures are neural fuzzy systems and genetic fuzzy systems.This augmentation process takes place between approximate reasoning method of fuzzy systems with learning and adaptation abilities of neural network and evolutionary algorithm.

KEYWORDS

Fuzzy graphs ,fuzzy modeling, fuzzy rule-based systems, Genetic algorithm & Tuning,FRBS,Neural Network.

I. INTRODUCTION

Fuzzy systems have been successfully implemented to problems related to classification, modeling and control and wide range of applications. In most of the cases the key for the success is the ability of the fuzzy systems to incorporate human expert knowledge.

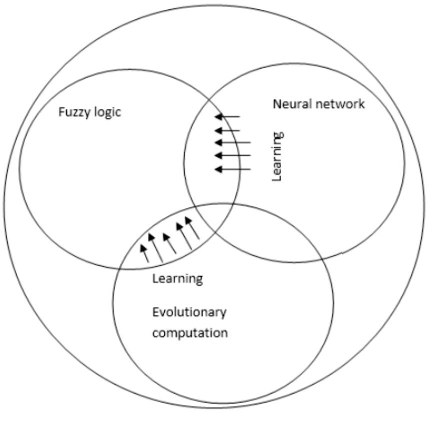

Figure -1

Typically a fuzzy systems have two components –a discrete one[1], the rules and on the other hand a continuous one known as fuzzy sets. Therefore fuzzy logic has proved to be very useful tool for representing human knowledge by means of mathematical expressions. The optimization of involved parameters has been one of the most investigated problems in the theory of fuzzy expert systems.

Fuzzy systems are rule based systems which are capable of dealing with imprecise information. There advantage is that nearly everything can be kept interpretable for humans. Thus prototyping [2] can be done very easily and fast. It takes a lot of time to tune all the involved parameters- a problem which becomes more worse with increasing complexity [3] of the system.

Fuzzy logic System:

Fuzzy logic is a unique soft computing method which simultaneously manages numerical data as well as linguistic knowledge. This unique feature has led it to be called "computing with words". People use fuzzy logic to arrive at decisions in the complex settings in which they operate. The fuzzy concepts could be numerically quantified using exact weight bounds and exercise bounds. However human reasoning does not operate using such numbers and still often reaches the surprisingly accurate decisions using fuzzy rules.

A Fuzzy Logic is a mathematical tool for dealing with terms such that "uncertainty" and "imprecision". It presents an idea by giving an effective & efficient conceptual framework so as to deal with the problem of knowledge base representation in an environment of both uncertainty and imprecision.

Why use Fuzzy Logic (FL)?

The conventional approaches to knowledge representation are based on bivalent logic. The major drawback of this approach is their inability to come to grips with the issue of uncertainty and imprecision. Besides this following key points can also be addressed for adopting fuzzy logic.

- It can be used as the basis for the representation of different forms of knowledge systems
- It can also be used to model the interactions and relationships among the system variables
- To model common sense reasoning

Taxonomy of Genetic Fuzzy Systems:

The following (Figure-2) depicts the recent taxonomy of Genetic Fuzzy Rule Based System.

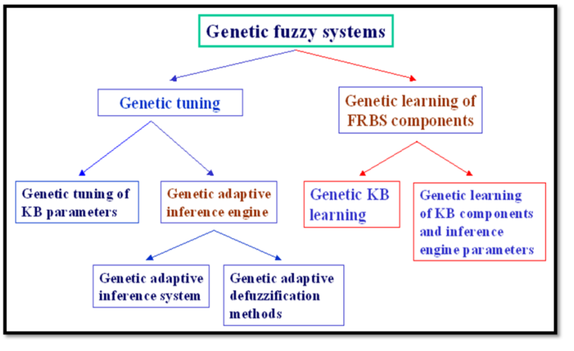

Figure-2: Recent Taxonomy of Genetic Fuzzy Rule Based System

Advantages of using fuzzy logic in designing Rule Based System

There are two essential advantages for the design of rule-based systems with fuzzy sets and logic:

- the key features of knowledge captured by fuzzy sets involve handling uncertainty, and
- inference methods become more robust and flexible with approximate reasoning methods of fuzzy logic.

Genetic Algorithm:

- Genetic Algorithm are general purpose search algorithms which uses principles used by natural genetics to evolve solutions to problems. The fundamental concept is to maintain a population of chromosomes (representing candidate solutions to the concrete problems being solved) that evolves over time through a process of competition and controlled variation.
- A GA initiates with a population of randomly generated chromosomes, and move forward 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.

Principle of Genetic Algorithm:
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.

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.

II. LITERATURE REVIEW

Genetic Fuzzy Rule Based System: Fuzzy linguistic descriptions are formal representations of systems made through fuzzy IF-THEN rules. They encode knowledge about a system in statements of the form-

IF(a set of conditions) are satisfied THEN (a set of consequents) can be inferred.

EXAMPLE: ***If*** there is rainfall or sunny day ***then*** you must carry an umbrella.

A number of papers have been devoted to the automatic generation of the knowledge base of a FRBS using GAs. The key 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.

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 find 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. As an example, the KB of a descriptive 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.

Genetic Tuning:
Tuning of the scaling functions and fuzzy membership functions is an important task in FRBS design.Parameterized scaling functions and membership functions are adapted by the GA according to a fitness function that specifies the design criteria in a quantitative manner.

As previously said, tuning processes assume a predefined RB and have the objective of finding a set of optimal parameters for the membership and/or the scaling functions . It is also Possible to perform the tuning process a priori, i.e., considering that a subsequent process will derive the RB once the DB has been obtained, that is a priori genetic DB learning.

Tuning scaling functions:
Scaling functions applied to the input and output variables of FRBSs normalize the universes of discourse in which the fuzzy membership functions are defined. Usually, the scaling functions are parameterized by a single scaling factor or a lower and upper bound in case of linear scaling, and one or several contraction/dilation parameters in case of non-linear scaling. These parameters are adapted such that the scaled universe of discourse better matches the underlying variable range.

Genetic learning of rule bases:
Genetic learning of RBs assumes a predefined set of fuzzy membership functions in the DB to which the rules refer to by means of linguistic labels (Fig-3). It only applies to descriptive FRBSs, as in the approximate approach adapting rules is equivalent to modify the membership functions.

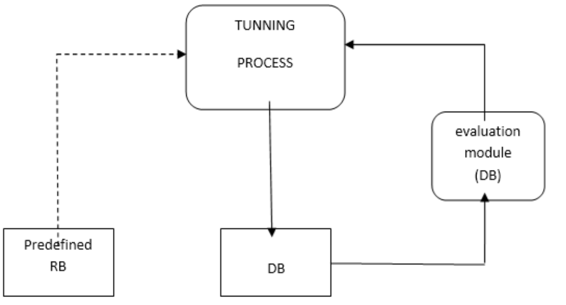

Figure-3: Tuning the data base.

The three **learning** approaches described in previous section can be considered to learn **RBs:** Michigan approach, Pittsburgh approach, and iterative rule learning approach. The RB can be represented by a relational matrix, a decision table ,or a list of rules .

Representations through relational matrix and decision table are only useful when the system has a reduced number of variables, since they lead to an unaffordable length of the code when having more than two or three input variables. The result is a monolithic code that can be only managed by the Pittsburgh approach.

The list of rules is the most used representation, adopts quite different codes for the individual rules, and can be adapted to the three learning approaches. Often the number of rules in the list is variable (having in some cases an upper limit). A common approach to code individual rules is the use of the disjunctive normal form (DNF) represented in the form of a fixed length binary string. DNF rules are also considered when working with variable length codes based on messy GAs. With a structure of list of rules, the chromosome can be generated by concatenating the code of individual rules (Pittsburgh, where each chromosome codes a RB) or will contain the code of a single rule.

Genetic fuzzy neural networks:
Genetic fuzzy neural networks are the result of adding genetic or evolutionary learning capabilities to systems integrating fuzzy and neural concepts. The result is a genetic-neuro-fuzzy system (or a genetic fuzzy neural network).

The usual approach of most genetic fuzzy neural networks found in the literature is that of adding evolutionary learning capabilities to a fuzzy neural network that usually is a feed-forward multilayered network to which, previously ,some fuzzy concepts were incorporated. The result is a feed-forward multilayered network having fuzzy and genetic characteristics [7,27,37,53,15].

Genetic fuzzy neural networks incorporate fuzzy numbers as weights, perform fuzzy operations in the nodes of the network, and/or consider fuzzy nodes to represent membership functions. In addition, the learning process uses GAs to obtain the weights of the neural network, to adapt the transfer functions of the nodes, and/or to adapt the topology of the net.

A different approach can be found in where an adaptive mechanism is proposed based on the concept of perpetual evolution. Here, adaptive control architecture uses evolutionary learning for initial learning and real-time tuning of a fuzzy logic controller. The initial learning phase involves identification of an artificial neural network model of the process and subsequent development of a fuzzy controller with parameters obtained via a genetic search.

III. PROBLEM IDENTIFICATION AND STATEMENT

Fuzzy Systems are highly applicable for modeling real world problems, like control ,classification, robotics etc. The ultimate target of the fuzzy systems is to deal with the uncertainty inherent in the real world problems, more specifically linguistic computation based control. But these fuzzy systems may be more accurate in their functioning if we design them using evolutionary approaches,

specifically Genetic Algorithms.
In this proposal the major focus would be on the following issues:

1. Effective Interpretable Encoding Scheme for the Fuzzy systems in Evolutionary Environment.
2. Consideration of Interpretability enhancement maintaining competitive accuracy.

Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end. Fuzzy logic can model nonlinear functions of arbitrary complexity. You can create a fuzzy system to match any set of input-output data. Fuzzy logic can be blended with conventional control techniques.

IV. CONCLUSION

This work presents a new methodology (HILK) for building knowledge bases with a good balance between accuracy and interpretability. It sets a general framework where a KB may include knowledge extracted from different sources. Two kinds of knowledge, expert knowledge and knowledge extracted from data are considered. They convey complementary information, and their fusion can lead to compact and robust knowledge bases. The fuzzy logic formalism allows the expression of both types of knowledge using the same linguistic variables.

It should be noted that HILK has been implemented as open source software in a tool named KBCT. It has been successfully applied in robotics for diagnosis of motion problems, telemedicine application.

In consequence, KBCT is an important contribution derived from this dissertation. Notice that all results presented in this document were reached using that tool.

Obtained results are compared with those achieved by other well known techniques, Naïve Bayes and C4.5. The comparison shows that both results are comparable in terms of accuracy, but HILK ones are usually much better in terms of interpretability. This methodology is thought for solving problems where both expert knowledge and experimental data are available, and KB interpretability is of prime importance.

V.FURTHER DEVELOPMENTS & FUTURE SCOPE

Some futuristic research lines have been identified that encourage to lead the enhancement of the methodology adopted–

1. Feature Selection. It would be useful in problems that involve a huge number of inputs. HILK makes possible somehow a selection of variables along the entire modeling process.

2.Automatic selection of the most suitable number of labels per variable. Currently we ask the experts regarding the right number of labels according to their experience. Then we select the best induced partition for that number. As a result the use of a granularity search method previous to the partition generation phase could help to get better solutions.

3.Interpretability. The fuzzy system built to measure interpretability can be upgraded by considering two main aspects. First, how to assess the influence of the selected fuzzy operators in the interpretability evaluation. Second how to compute the interpretability of hierarchical fuzzy systems.

4.Completeness Analysis. Initial experiments depicts that the final knowledge bases achieved by HILK methodology are not always complete. It may be due to those situations not initially considered by the experts. Completing the KB to cover all possible situations means adding new rules which results in the reduction of the KB interpretability. Therefore a deeper analysis is needed in order to check if completing the KB is worthy of consideration depending upon the nature of the problem to solve.

5.Regression Problems. HILK methodology could be applied on regression problems considering the two main aspects. Firstly the consistency analysis must be reviewed because new kinds of conflicts can appear. Secondly a new accuracy index has to be defined.

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