The Effective Use of Diverse Rule Bases in Fuzzy Classification

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***Abstract*— This paper is concerned with the synthesis of diverse rule bases for fuzzy classification. An immune-inspired approach for combinatorial optimization, capable of controlling the size and diversity of the population along the search, is applied to generate multiple high-quality solutions. A preliminary comparison of the obtained rule bases indicates the existence of inconsistency, mainly characterized by the presence of rules with the same antecedent part and distinct consequent parts. Based on a winner-takes-all reasoning method, the effective portion of the input space allocated to each rule will depend on a competitive procedure. So rules with the same antecedent part in distinct rule bases may fire at distinct portions of the input space, and possibly with distinct consequent parts. This presumed disadvantage, when interpretability issues are concerned, can be assertively explored to produce an ensemble of fuzzy classifiers, with increment in performance precisely for the same reason. High-quality and diverse solutions are essentially the basic requisites for successful implementation of ensembles. A qualitative disadvantage may then become a quantitative advantage.**

I. Introduction

Fuzzy Systems are fundamental methodologies to represent and process linguistic information, with mechanisms to deal with uncertainty and imprecision. With such remarkable attributes, fuzzy systems have been widely and successfully applied to control, classification and modeling problems [1] [2].

One of the most important tasks in the development of fuzzy systems is the design of its knowledge base. An expressive effort has been devised lately to develop or adapt methodologies that are capable of automatically extracting the knowledge base from numerical data. Particularly in the framework of soft computing, significant methodologies have been proposed with the objective of building fuzzy systems by means of genetic algorithms (GAs).

Genetic Algorithms have demonstrated to be a powerful tool to perform tasks such as [3]: generation of fuzzy rule base, optimization of fuzzy rule bases, generation of membership functions, and tuning of membership functions. All theses tasks can be considered as optimization or search processes. Fuzzy system generated or adapted by genetic algorithms are called Genetic Fuzzy Systems [4]. The combination of Fuzzy Systems with Genetic Algorithms has great acceptance in the scientific community, once these algorithms are robust and can efficiently search large solution spaces [5].

However, a basic GA together with a significant portion of its variants are not effective in dealing with multimodal optimization [6]. And a simultaneous search for multiple high-quality solutions is strongly desired in certain applications of fuzzy classification systems [7].

A relatively novel computational paradigm, namely Artificial Immune System (AIS), was originated from attempts to model and apply immunological principles to problem solving in a wide range of areas such as optimization, data analysis, computer security and robotics [8] [9]. As advantages of AIS over other search strategies we have its ability to maintain population diversity and to find many good solutions simultaneously, if they exist.

The authors have already investigated the application of an AIS, namely Copt-aiNet [10], for generating at the same time a pool of diverse and accurate fuzzy classification systems designed to produce complementary aspects of the solution. The results, advantages and usefulness of the proposal have been reported in the literature [11].

Now, the authors analyze interpretability issues associated with the fuzzy rule bases of the several fuzzy systems generated by the Copt-aiNet. The term incoherence here is designed to represent scenarios characterized by fuzzy systems with rules having the same antecedent part and distinct consequent parts. In the competitive nature of the winner fuzzy rule reasoning method [12], the rules of the same rule base compete with each other to decide which one will be fired at each portion of the input space. So rules with the same antecedent part in distinct rule bases may fire at different portions of the input space, and possibly with divergent consequent parts. At a first moment, divergent rule bases are not desired in fuzzy classification, since inconsistency represents a disadvantage when interpretability issues are considered. The authors show then how to turn this qualitative disadvantage into a quantitative advantage, building an ensemble of fuzzy classifiers, with improvement in performance. The successful implementation of ensembles is related to the quality and diversity of their components.

This paper is organized as follows. Section II shows the fuzzy classification rule format and the fuzzy reasoning method employed. Section III describes the Copt-aiNet algorithm. Section IV presents the application of Copt-aiNet to the generation of fuzzy rule bases. Experimental results are presented and discussed in section V. Finally, section VI draws some concluding remarks.

II. Fuzzy Classification Rule Format and Fuzzy Reasoning Method

This section describes the fuzzy rule format and fuzzy reasoning method employed in this work.

We use fuzzy rules for pattern classification problems of the following type:

R_k: IF X_1 is A_{k1} and ... and X_n is A_{kn}, THEN $Class_j$

where R_k is the rule identifier, $X_1, \ldots, X_n$ are attributes of the input pattern, A_{ki} is the linguistic term defined by a fuzzy set used to represent the attribute X_i in rule R_k, and $Class_j$ represents the class.

In a Fuzzy Classification System, the reasoning method is based on fuzzy logic. It derives conclusions from a set of fuzzy rules and a pattern. The Winner Fuzzy Rule Reasoning Method [12] is adopted here to classify a new pattern as described below.

Let $e_p = \{a_{p_1}, a_{p_2}, ..., a_{p_n}\}$ be the pattern to be classified, $a_{p_1}, ..., a_{p_n}$ the values of the corresponding attributes $X_1, \ldots, X_n$, and $R = \{R_1, R_2, ..., R_S\}$ the fuzzy rule set. The Winner Fuzzy Rule Reasoning Method is performed by the following steps:

Step 1: Calculate the compatibility degree, *Compat(*R_k*,*e_p*)*, between the pattern e_p and each rule R_k, *k*=1...*S*, applying a T-norm [1] [2] to the membership degree of the pattern attribute values, a_{p_i}, in the corresponding fuzzy sets that appear in the antecedent part of the rule R_k, A_{ki}, *i*=1...*n*.

$$\text{Compat}(R_k, e_p) = \text{T}\ (\mu_{A_{k1}}(a_{p_1}), ..., \mu_{A_{kn}}(a_{p_n})) \tag{1}$$

Step 2: Find the rule with higher compatibility degree with the given pattern,

$$\text{Max}\{\text{Compat}(R_k, e_p)\ \} \qquad , k=1...S \tag{2}$$

Step 3: The pattern e_p will be classified in the class $Class_j$, such that $Class_j$ is the class of the rule R_k that possess the highest compatibility degree with the pattern.

If two or more rules present the same compatibility degree with the pattern, but different consequent parts, then the rule with the smallest index will be fired. Although this fuzzy reasoning method seems too simple, it presents a satisfactory level of accuracy and its simplicity may contribute to understand how it derives the conclusions.

III. The Copt-aiNet Algorithm

This section presents the Copt-aiNet (Artificial Immune Network for Combinatorial Optimization) algorithm and the immune inspirations utilized to develop it.

The Copt-aiNet was proposed by Gomes et al. [10] for solving combinatorial optimization problems. The authors demonstrated empirically the suitability of the algorithm and presented results with improvement in performance over other approaches.

The Copt-aiNet is based mainly on two immune principles, namely clonal selection [13] and immune network [14]. The clonal selection theory states that when an antigen invades the organism, some antibodies that recognize this antigen start proliferating. The higher the affinity between an antibody and an antigen, the more offsprings, called clones, will be generated. During proliferation, the clones suffer mutation with rates proportional to their affinity with antigens: the higher the affinity, the smaller the mutation rate, and vice-versa. The other important theory is the so-called immune network theory, which proposes that antibodies are not only capable of recognizing antigens, but they are also capable of recognizing each other. When an antibody is recognized by another one, it is suppressed. These two theories are fundamental to the maintenance of diversity in the population and to the search for multiple good solutions based on automatic definition of the population size at each generation.

The Copt-aiNet algorithm may be explained by the following steps:

Step 1 - Generation of the initial population: the initial population is constructed randomly. Each antibody represents a feasible solution to the problem. Initially the population contains 20 individuals and it is allowed to grow and shrink dynamically.

Step 2 - Population evaluation: the fitness value of each antibody is calculated using the objective function.

Step 3 - Clonal Selection: each antibody gives origin to a number of clones, denoted by *C*. This number is proportional to the antibody fitness value.

Step 4 - Hypermutation: the clones generated in the previous step suffer a mutation process. The mutation rate of each clone is inversely proportional to its fitness: clones with higher fitness will be submitted to lower mutation rates and vice-versa.

Step 5 - Suppression: the antibodies interact with each other in a network form by determining their similarity. If two or more antibodies are similar within a similarity threshold, the antibody with lower fitness value is eliminated from the population. This process avoids redundancy and therefore tends to preserve population diversity.

Step 6 - If none of the *k* best solutions is improved along a predefined number of iterations, all the antibodies in the population suffer a maturation process. During the maturation process, the antibodies suffer a series of guided mutations in order to better match the antigens. This process is implemented by a local search heuristic. In Copt-aiNet, a tabu search heuristic [15] is employed as a local search procedure.

Step 7 - Return to Step 2 if the stopping condition was not met.

IV. The Copt-aiNet Algorithm for Fuzzy Systems Designing

This section describes the application of the Copt-aiNet algorithm to fuzzy rule bases generation, once the automatic building of fuzzy rules is usually interpreted as a combinatorial optimization process [16]. Starting from a dataset representing samples or examples of the problem and with membership functions previously defined, the proposed method applies the Copt-aiNet to find suitable fuzzy rule bases that correctly classify these examples. Next, we detail the fuzzy membership function generation, the rule bases coding scheme, the fitness function, and the hypermutation and suppression operators adopted in the present work.

- **Definition of Membership Functions**

In this work the linguistic terms associated with each input attribute are represented by triangular membership functions uniformly distributed in the universe of discourse. In Figure 1 there is an example of this kind of fuzzy partition, where the variable is represented by 3 linguistic terms (fuzzy sets).

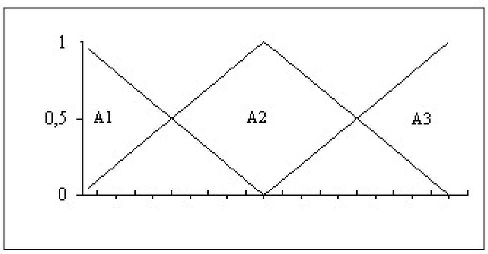

Fig. 1. Example of fuzzy partition

We adopted triangular membership functions for the sake of simplicity though other shapes might have been defined.

- **Coding of Fuzzy Rule Base**

Each antibody encodes an entire fuzzy rule base while the antigen represents the training patterns. The rules are coded by integer numbers that represent the index of fuzzy sets that appear in the antecedent and consequent part of the rule. The number 0 is associated with the *"don't care"* condition.

For instance, suppose a classification problem where the patterns are described by three attributes - X_1, X_2, and X_3 - and one class - C_j. The attributes are associated with the domains $D_1 = \{A_{11}, A_{12}, A_{13}\}$, $D_2 = \{A_{21}, A_{22}, A_{23}\}$, and $D_3 = \{A_{31}, A_{32}, A_{33}\}$, respectively and the classes are $C = \{Class_1, Class_2, Class_3\}$. Now, consider the following rule base to this problem:

R_1: IF X_1 is A_{12} and X_2 is A_{23} and X_3 is *"don't care"*, THEN $Class_1$

R_2: IF X_1 is A_{13} and X_2 is A_{21} and X_3 is A_{31}, THEN $Class_2$

$\vdots$

R_k: IF X_1 is *"don't care"* and X_2 is A_{22} and X_3 is A_{31}, THEN $Class_3$

Figure 2 presents an antibody that encodes this rule base. Each rule is represented by 4 genes, where the first three genes indicate the index of the fuzzy sets of the attributes X_1, X_2, X_3, and the fourth gene represents the class.

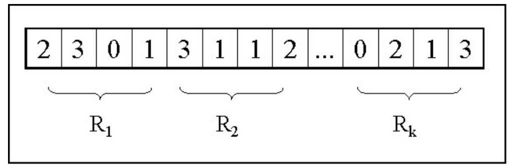

Fig. 2. Example of antibody

The use of the *"don't care"* condition provides better generalization capability of correctly classifying new patterns. Besides, the introduction of *"don't care"* has also an important effect on rule interpretability, once these rules have fewer attributes on the antecedent part. Short rules can be more easily understood by human beings than long rules with many attributes [17].

- **Initial Population**

The initial population is randomly generated and each individual adopts the representation depicted in Figure 2. At each position in the string a random number from 0 to q_i is chosen,, where q_i is the number of fuzzy sets to represent the *i-th* attribute.

- **Fitness Function**

The fitness function is defined based on performance of the fuzzy rule base, calculated as a function of the number of training patterns correctly classified, using the fuzzy reasoning method presented in section II. The fitness function is expressed by:

$$\text{Fit } (Ab_i) = NPC(Ab_i) \tag{3}$$

where *NPC(Ab_i)* is the Number of Patterns Correctly Classified by the fuzzy rule base coded in the antibody Ab_i.

- **Cloning**

All antibodies of current population suffer a cloning process. The number of clones per antibody is proportional to its fitness value (affinity with antigen). Higher fitness corresponds to a higher number of clones. The function used to implement this procedure is presented in equation (4).

$$\text{C}(Ab_i) = \begin{cases} \text{Min\_C} & \text{if Fit}(Ab_i) \leq (Max\_Fit * 0.3) \\ \text{Max\_C} & \text{if Fit}(Ab_i) \geq (Max\_Fit * 0.7) \\ \frac{\text{Fit(Ab}_i)}{\beta} & \text{otherwise} \end{cases} \tag{4}$$

where Min_C and Max_C are the minimum and maximum number of clones, respectively. Fit(Ab_i) is the fitness value of antibody Ab_i, Max_Fit is the highest fitness value found in the current iteration and β is a parameter that can vary during the process. The values 0.3 and 0.7 were obtained empirically by preliminary experiments.

- **Hypermutation**

The clone mutation rate is inversely proportional to its affinity with antigen. The mutation rate is given by:

$$P_{mut}(Ab_i) = Max\_P_{mut} * \frac{(Max\_Fit - Fit(Ab_i))}{(Max\_Fit - Min\_Fit)} \quad (5)$$

where $P_{mut}(Ab_i)$ is the mutation rate for *i-th* clone, Max_P_{mut} is the highest value that mutation rate can assume, $Fit(Ab_i)$ is the fitness of clone i, Max_Fit is the highest fitness value found in the current iteration, and Min_Fit is the lowest fitness value found in the current iteration.

- **Suppression**

In this phase, similar antibodies are eliminated in order to avoid redundancy and thus maintain diversity. The degree of similarity between the antibodies is measured based on their individual outputs. If two or more classifiers classify correctly the same patters and also misclassify the same patterns, the degree of similarity is maximum. Antibodies with a degree of similarity above a certain threshold are eliminated from population, being kept only the one with higher fitness.

- **Stopping Condition**

A maximum number of generations is adopted here as the stopping condition.

V. Experimental Results

This section outlines empirical evidences to support similar performance of divergent fuzzy rules when applied to the same classification problem. We applied the Copt-aiNet algorithm, presented in section IV, to generate fuzzy classification systems for an artificial dataset, available on http://www.lbic.fee.unicamp.br/homepage/downloads/artif.txt, and for two well-known classification problems from UCI Repository of Machine Learning Databases [18].

Table I summarizes the knowledge domain characteristics giving the total number of instances, the number of attributes, and the number of classes per dataset. The Bupa and Iris datasets are well-known and frequently used in machine learning tasks.

TABLE I
Dataset Characteristics

Dataset	# Instances	# Attributes	# Classes
Artificial	3000	2	3
Bupa	345	6	2
Iris	150	4	3

The Artificial dataset was created to perform preliminary experiments. Figure 3 gives a graphical representation of this dataset.

Each dataset was partitioned as follows: 80% for training and 20% for validation. This partitioning was performed randomly in each run of the algorithm. For each dataset, we applied the algorithm 10 times so that you have 10 distinct partitions at each execution.

Firstly, we demonstrate the ability of Copt-aiNet to design fuzzy classification systems. For all experiments, the maximum number of generations was 1000. Table II presents an

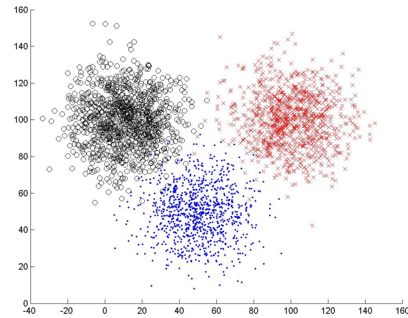

Fig. 3. Artificial Dataset

average of the results over 10 executions for test data using the best classifier obtained in each execution. The 4th column of Table II is the average number of rules per rule base. Note that the rule bases are composed of a few number of fuzzy rules.

TABLE II
Experimental results

Dataset	Classif.(%)	Std. Dev.	# Rules
Artificial	97.1	1.87	5
Bupa	72.4	1.24	9
Iris	93.5	0.96	6

From Table II we can see that the immune algorithm is able to generate fuzzy systems with a satisfactory level of accuracy. For Bupa and Iris datasets, the results obtained are better or very close to results from other fuzzy classification systems reported in the literature. A fuzzy system generated by an AIS in Alves et al. [19] achieved 57.4% of accuracy in Bupa dataset. A genetic fuzzy system was applied to Iris dataset classifying correctly 96.4% of test patterns in Ishibuchi and Yamamoto [20].

As expected, the Copt-aiNet found not only one but many high-performance fuzzy classification systems in a single run. Table III shows the average individual performance of seven fuzzy classifiers generated by Copt-aiNet for the Iris dataset.

TABLE III
Individual results for the Iris dataset

Fuzzy Classifier	Classification rate
a	89.1 %
b	91.7 %
c	90.3 %
d	92.4 %
e	92.4 %
f	93.5 %
g	93.0 %

From Table III we can see that the seven fuzzy classifiers present similar performance. Intuitively, this would make us believe that the rules would be similar and agree with each other. However, as it is shown in Figure 4 this actually does not happen. Although we can see some similar rules, the number of incoherent rules is high. We also observed that this phenomena occurred not only for Iris but for all the datasets studied here.

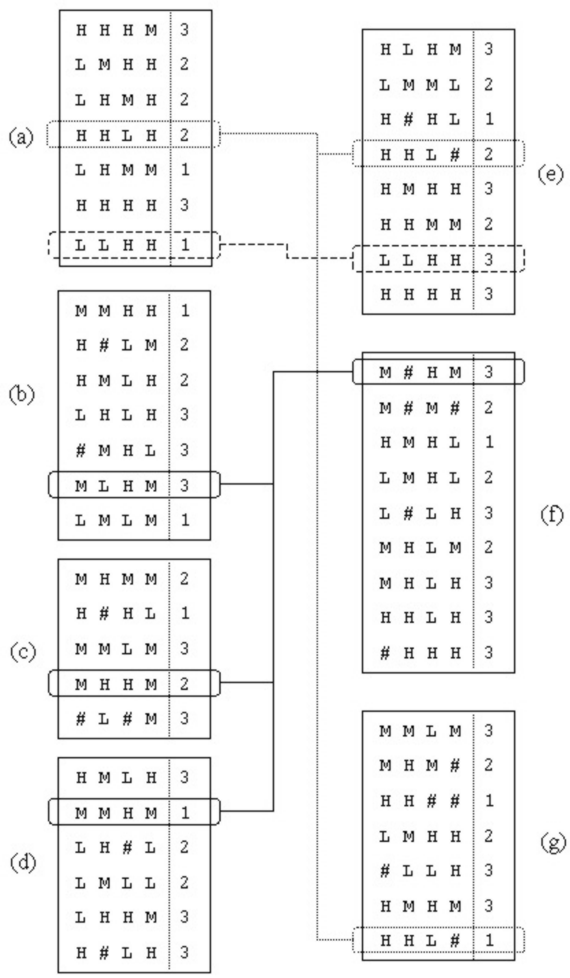

Fig. 4. Rule bases produced by a single run of Copt-aiNet

In Figure 4, each box represents a fuzzy rule base. The first four columns correspond to the antecedent parts (sepal length, sepal width, petal length, and petal width) of the rules, and the last column, the classes. In the antecedents, H means that the value of this attribute is HIGH, M means that the value is MEDIUM and L means that it is LOW. In the consequent, 1, 2 and 3 means class setosa, virginica and versicolor, respectively. The symbol "#" represents the "don't care" condition. The connected rules indicate some of the incoherences found in the rule bases (same antecedent and different consequent parts).

A possible explanation for similar performance of diverse rule bases lies on the interaction established by the rules in each rule base. Considering two distinct rule bases, each one containing a rule with the same antecedent part, nothing can be anticipated about the effective portion of the input space that will be allocated to those rules, because each rule will compete with the remaining ones. So, even with the same antecedent part, rules may fire at distinct portions of the rule space, given the rule base. Under this circumstance, rules with the same antecedent part, but belonging to distinct rule bases, may contain distinct consequent parts.

At a first glance, these divergences between rule bases become a disadvantage when interpretability issues are considered. On the other hand, in terms of classification performance, obtaining diverse fuzzy classifiers to the same problem give us the possibility of building ensembles of classifiers. An ensemble [21] [22] is a computational paradigm where alternative proposals, called components of the ensemble, combine their individual outputs into a single one to derive a solution to a given problem. The reasons for combining multiple proposals are compelling, because they may implicitly represent different useful aspects of the intented solution.

Figure 5 depicts a general ensemble framework. Suppose it is operating as an ensemble of classifiers. Each component of the ensemble is a fuzzy classifier independently proposed and they can operate in isolation. For each input *x*, the output y_i, *i=1,...,M*, generated by the *M* components is combined using the majority voting method to produce the output of the ensemble, *y*. In this combination method, a pattern is classified in the class C_j if C_j is the individual output of the majority of components.

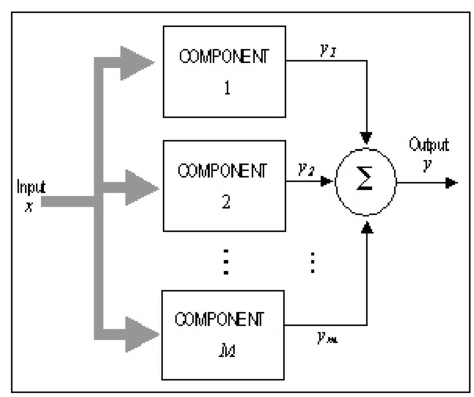

Fig. 5. Scheme of an ensemble

The good performance of an ensemble relies on the quality and diversity of its components. We have presented previously that high-performance and diverse fuzzy classifiers were obtained, what leads us to build an ensemble, aiming to achieve an improvement in performance. The results obtained for each dataset are shown in Table IV.

TABLE IV
RESULTS USING ENSEMBLES

Dataset	Classif.(%)	Std. Dev.
Artificial	98.8	0.90
Bupa	74.4	0.78
Iris	97.2	1.02

As expected, we can see from Table IV that the ensemble of fuzzy classifier systems improved the classification accuracy, outperforming the single best classifier for all datasets.

Even presenting results that outperform similar approaches (devoted to fuzzy classification systems that adopt the same reasoning method and the same partition of the data set for training and testing), the purpose here is not to surpass every other approach to solve the classification problems considered. For example, a Takagi-Sugeno version of a genetic fuzzy system proposed in Delgado et al. [23] outperforms our approach in the Iris data set and may possibly produce superior results in the other data sets too.

The main contribution here are: i) the proposal of a systematic way to generate diversity in genetic-like fuzzy systems by means of an immune-inspired combinatorial optimization procedure; and ii) the proper exploration of this diversity using ensembles of fuzzy classification systems.

An interesting aspect of the Copt-aiNet algorithm is that the diversity level can be fine-tuned by the adjustment of the suppression threshold.

VI. Concluding Remarks

This work presented an immune-based learning method for obtaining fuzzy classification systems. From numerical data and with membership functions defined previously, the algorithm evolves a population of fuzzy rule bases using the clonal selection, hypermutation and immune network principles. The multimodal feature of the presented algorithm allows many high-performance and diverse solutions to be achieved.

Experiments on three datasets have demonstrated that the immune algorithm presented here is able to generate accurate and diverse fuzzy systems on each run. Being a disadvantage in qualitative aspects, mainly in terms of interpretability and consistency, diversity may represent a clear quantitative advantage, mainly in terms of performance. The high-quality and diverse rule bases can compose an ensemble of classifiers with significant gain in performance when the individual outputs are combined using majority voting.

The experimental results can be further improved in several aspects. Formal analysis and statistical methods could be applied to derive more robust conclusions. For example, we expect that the comparison of several fuzzy rule bases can help to identify which variables are more relevant/irrelevant to the classification task, observing the quantity of "don't care" conditions present in each rule base. We also intend to use other formats for the membership functions, together with different fuzzy reasoning methods, and apply the proposed methodology to datasets with higher dimensionality, in order to verify the scalability of the algorithm.

Acknowledgements

This work has been supported by grants from Fapesp, Capes, and CNPq

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