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Inconsistency in Fuzzy Rulebase: Measure and Optimization

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Abstract

Rule inconsistency is an important issue that is needed to be addressed while designing efficient and optimal fuzzy rule bases. Automatic generation of fuzzy rules from data sets, using machine learning techniques, can generate a significant number of redundant and inconsistent rules. In this study we have shown that it is possible to provide a systematic approach to understand the fuzzy rule inconsistency problem by using the proposed measure called the Commonality measure. Apart from introducing this measure, this paper describes an algorithm to optimize a fuzzy rule base using it. The optimization procedure performs elimination of redundant and/or inconsistent fuzzy rules from a rule base.

Key Words: Fuzzy rulebase, Fuzzy rule inconsistency, Commonality measure, Fuzzy rule base optimization.

I. Introduction

Validation of rule bases is an important research area in knowledge base systems as it ensures the correctness and robustness by detection of anomalies. Anomalies in a rule base or a knowledge base can be detrimental to rule based system's performance. Anomalies like conflicting rules, redundant rules, inconsistency of rules, coherency factors, and a few more often exist in rule bases. Among them, inconsistency of rules is one of the major reasons for rule base system failure. Definitely, it can be argued that such situations may be valid for systems based on the classical logic. Can fuzzy logic-based systems handle such uncertain situations? To some extent it can, but that does not root out the basic nature of inconsistent (absurd) rules that may exist in a fuzzy rule base.

Inconsistent rules are generated in fuzzy rule bases mainly because of two reasons. Either from time to time different pieces of knowledge from different experts are added upon the existing knowledge base, or by using machine generated fuzzy rules through clustering and data mining algorithms for different types of data sets.

Designers of fuzzy systems have often evaded the problem and have worked around by tuning membership functions of their fuzzy sets. Zadeh defined consistency of fuzzy sets by using the maximum possibility of two intersecting fuzzy sets [15]. Pedrycz extended that idea by using conditional possibility and thresholding mechanisms to remove inconsistent rules [9]. Partially or totally inconsistent fuzzy rules have been discussed by Nguyen et. al. [8]. Yager and Larsen [13] have proposed reflecting input method that would discover potentially hidden anomalies by using the principles of the classical logic.

In this paper, we are interested in eliminating undesirable rules, undesirable in a sense of being redundant or inconsistent. Section 2 briefly highlights some of the existing approaches that have been undertaken to understand and solve this problem. However, we like to understand this problem by focusing on commonalities that exist among rules. We propose a measure called the Commonality measures for fuzzy sets and fuzzy rules in Section 3. In Section 4, we use these measures in the construction of an algorithm to remove redundant and/or inconsistent rules.

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II. Earlier Work

Zadeh has defined the inconsistency in terms of heights of intersecting fuzzy sets [15]. Yager and Larsen [13] have introduced the reflecting on the input method, and this method has been discussed again by Dubois et. al [4].

Pedrycz's original approach [9] was to use conditional possibility measures for both antecedents and consequents to determine measure of inconsistency of fuzzy rules. Scarpelli et. al. [10] have enhanced Pedrycz's work [9]. Usually most of the work done so far has a common framework. They all would match on something on both sides of fuzzy rules. For instance, they establish some sort of similarity between respective antecedents and consequents. In other words, it means:

$$F(A_1, A_2) \rightarrow F'(B_1, B_2), \quad (1)$$

for two fuzzy rules $A_1 \rightarrow B_1$ and $A_2 \rightarrow B_2$ Usually F and F' are some similarity based match. Height is one of such match functions that have been often used in most of the previous works [4, 9].

Dubois, Prade, and Ughetto [4] have addressed the problem of coherence and redundancy of parallel fuzzy rules. They have justified their reasoning for various different kinds like gradual rules [3], possibility rules, certainty rules, etc. In [4] they also proposed practical coherence tests for fuzzy rules, but it seems that the construction of core is bit nebulous.

Bien and Yu [1] have proposed a method to extract core information from a fuzzy control rule base having some inconsistent rules. They have shown through simulation studies that inconsistent control rules can be effectively utilized by using their method. Their method is founded on an inference-oriented methodology that is based on statistical concepts.

Recently, Wang and Cho [11] developed an input space partitioning method for structure identification of fuzzy modeling. They have proposed a method that is based on genetic algorithms. The method is reported to generate a set of less inconsistent rules while satisfying the given accuracy requirement.

III. Commonality Measure

This section proposes a new measure to comprehend the fundamental nature of rule inconsistency in fuzzy rule bases. It is called as the Commonality Measure. When two fuzzy sets intersect, it is possible to use their shared information as source of common knowledge. Thus, the commonality measure extracts the common information shared by two fuzzy sets.

3.1 Preliminary Ideas

Before we define these measures for the evaluation of the consistency of fuzzy rules in a rulebase, we revisit few existing ideas that we need to explain these measures. One of them is the geometric distance in fuzzy sets, and the other is the notion of specific information content of a fuzzy set.

3.1.1 Geometric Representation of Fuzzy Sets

A fuzzy set can be represented as a point in a hyperspace of its membership functions (see Kosko [6]) and is often called as the geometric representation of fuzzy sets. The support set of a fuzzy set is implicitly assumed to be the universe of discourse. Kosko represented his fuzzy set as a fit vector [6]. The geometric properties in the membership-based hypercube follow the same principles of the Cartesian geometry. Similar to the distance defined in the Cartesian geometry, a distance between two fuzzy sets A and B is defined as an l^p-norm:

$$d(A,B) = \sqrt[p]{\sum_{i=1}^{n} (\mu_A(x_i) - \mu_B(x_i))^p} \quad (2)$$

where $p \in [1, \infty)$, and n is the cardinality of the universe of discourse. When p = 1, we get classical Hamming distance, and at $p \rightarrow \infty$ we have $\max_i(\mu_A(x_i) - \mu_B(x_i))$. Apart from the geometric representation, our measures use a well-known concept of specificity of fuzzy sets. Here we only provide the basic definition and the reader is encouraged to refer to [5, 6].

3.1.2 Specificity

Yager [14] defined specificity of a fuzzy set as:

$$Sp(A) = \int_0^{\alpha_{max}} \frac{1}{|A_\alpha|} d\alpha \quad (3)$$

where A_α is the α-cut and α_{max} is the largest membership grade in A. Among some of the important properties for $Sp(A)$, we note that it is bounded between [0,1]. A singleton set has specificity of 1, and for an empty set it is zero. Specificity increases for subsets with the same normal, but decreases for subnormal sets. There are other properties that can be found in [2, 12, 14]. Among other notable works using specificity, Kacprzyk used this measure to study fuzzy If-Then rules [7].

3.2 Commonality Measures

The above concepts are used here to define a new measure to evaluate the information contents based on common knowledge that exists among two pieces of information. We call this measure as the Commonality Measure. The commonality measure gauges the amount of common information that may exist between two fuzzy sets. It uses the concept of specific knowledge that is shared between two distinct pieces of information sources.

Definition: The commonality measure, $\phi(A,B)$, between two fuzzy sets A and B is defined by:

$$\phi(A,B) = 1 - e^{-\left(\frac{Sp(C)}{d(A,B)}\right)} \quad (4)$$

where C = T(A, B), and T is a t-norm.

The commonality measure is founded on the concept of evaluating common information while considering the relative knowledge from a spatial viewpoint. It estimates the relative comparison of pertinently common components of two fuzzy sets existing in the same universe of discourse. The distance measure enforces spatial evaluation in terms of distinctness between two fuzzy values within the same universe of discourse. The spatial information is required because it allows characterizing the information content in a relative sense.

The properties of this measure are easy to compute. For example, when two fuzzy sets are the same i.e., A = B, then we can have $\phi(A,B)=1$. It implies that both the fuzzy sets have maximum commonality. We also observe that when support sets are same but normals are different, the distance between the two fuzzy sets is nolonger zero. Thus, for only identical fuzzy sets we have the maximum commonality and that equals to one. The commonality measure is zero for two totally disjoint fuzzy sets.

Example 1: Consider two fuzzy sets A and B with the following fit vectors: A = (0, 0, 0, 0, 0.2, 0.4, 0.6, 0.8, 0.5, 0.3, 0.1, 0, 0, 0, 0, 0, 0), and B = (0, 0, 0, 0, 0, 0, 0, 0, 0, 0.4, 0.5, 0.8, 1, 1, 1, 0.5, 0) having the same universe of discourse X = (10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27). Consequently, we have C = T(A,B) = (0, 0, 0, 0, 0, 0, 0, 0, 0, 0.3, 0.1, 0, 0, 0, 0, 0, 0), and D = T*(A,B) = (0, 0, 0, 0, 0.2, 0.4, 0.6, 0.8, 0.5, 0.4, 0.5, 0.8, 1, 1, 1, 0.5, 0).

From the above fuzzy sets we compute $Sp(C)$=0.25, and $Sp(D)=0.17$. We also compute specificities of the original fuzzy sets $Sp(A)=0.35$ and $Sp(B)=0.22$ to evaluate the contrast measure. The l^2-norm based distance between the fuzzy sets is 2.35. Therefore, the commonality measure we get from these values is $\phi(A,B)=0.10$.

Once we evaluate the commonality measure between two fuzzy sets, it then becomes quite simple to generate commonality measures for the rules and rule bases. The respective commonality measures can be treated as indicators of the amount of common knowledge that is embedded in the rules and rule bases.

Let us consider a rule base RB, comprising of p conjunctive fuzzy rules with n antecedents and m consequents:

R_1: (x_1 is A_1^1),...,(x_n is A_n^1)→(y_1 is B_1^1),...,(y_m is B_m^1)

...

R_l: (x_1 is A_1^l),...,(x_n is A_n^l)→(y_1 is B_1^l),...,(y_m is B_m^l)

...

R_k: (x_1 is A_1^k),...,(x_n is A_n^k)→(y_1 is B_1^k),...,(y_m is B_m^k)

...

R_p: (x_1 is A_1^p),...,(x_n is A_n^p)→(y_1 is B_1^p),...,(y_m is B_m^p)

We can compute the commonality measure ϕ_i^{lk} for antecedent variable x_i with fuzzy sets A_i^l and A_i^k of the rules R_l and R_k, respectively. Similar computation is performed for other antecedents and consequents for a fuzzy rule.

Consider R_l and R_k from the above rule set. The commonality measure for the j^{th} antecedent of those two rules is given by:

$$\phi_{A_j}^{lk}=1-e^{-\left(\frac{Sp(T(A_j^l,A_j^k))}{d(A_j^l,A_j^k)}\right)} \quad (5)$$

The commonality measure for all antecedents for these two rules is given by:

$$\phi_A^{lk}=\sum_{j=1}^{n}\phi_{A_j}^{lk} \quad (6)$$

Similarly, the total commonality measure for all the consequents of the rules Rl and Rk is measured by:

$$\phi_B^{lk}=\sum_{i=1}^{m}\phi_{B_i}^{lk} \quad (7)$$

where $\phi_{B_i}^{lk}$ is the commonality measure for consequent fuzzy sets B_i^l and B_i^k for Rl and Rk.

Definition: Commonality of the two rules, R_l and R_k is defined by ϕ^{lk} as a normalized summation of the commonality measures of the antecedents variables and the consequent variables of the rules.

$$\phi^{lk}=\frac{\phi_A^{lk}+\phi_B^{lk}}{n+m} \quad (8)$$

Certainly, it is well observed that since $\phi_{A_j}^{lk}$ and $\phi_{B_i}^{lk}$ in (6) and (7) are less than or equal to 1, we have $\phi^{lk}\leq 1$. For any two identical rules, say, Rl and Rk, the commonality measure is $\phi^{lk}=1$. Existence of identical rules leads to redundancy of rules in a rule base. Therefore, in this paper we will refer to identical rules as redundant rules. It is important to deplete the rule base of redundant rules. By contrast, we have $\phi^{lk}=0$ for totally different rules. Otherwise, for any inconsistent rule we usually have $\phi^{lk}\in(0,1)$. It is to be noticed that more the rules become inconsistent, the more redundant they are.

A rule base is a collective entity. Thus, it is important to evaluate a rule in the presence of other rules in the rule base. The commonality measure ϕ^l of single rule Rl is computed as:

$$\phi^l=\sum_{k=1,k\neq l}^{p}\phi^{lk} \quad (9)$$

Once we compute commonality for an individual rule we also compute the total commonality measure of the entire rule base and is given by:

$$\phi_{RB}=\sum_{l=1}^{p}\sum_{k=l+1}^{p}\phi^{lk} \quad (10)$$

Using commonality is one of the viewpoints to study rule inconsistency and rule base optimization. It is also possible to use another viewpoint of evaluating the contrasting features of two pieces of knowledge to understand inconsistency that fuzzy sets and fuzzy rules induce.

IV. Optimizing Fuzzy Rule Bases

We will use the commonality measure to propose an optimization algorithm for the fuzzy rule base that has inconsistent rules. The optimization procedure described here is obtained by deleting some of the gradual rules that add to inconsistency and/or redundancy in the rule bases. Dubois and Prade have focused on incoherent and redundant rules as separate issue [4].

Consider Fig. 1, in which there are two rules with two antecedents and a consequent. We observe from the figure that the antecedent variables X_1 and X_2 of two fuzzy rules have the same antecedent fuzzy sets, but different consequent sets. This is an extreme example of inconsistent fuzzy rule. It is possible that such rules might be generated while using either opinions of different experts, or from various automatic rule generation algorithms.

In general, there are a few ad hoc mechanisms and procedures that are used by researchers to remove such anomalies in fuzzy rule bases [9, 10]. However, ad hoc methods based on thresholding mechanisms are of serious disadvantages. Firstly, how do we decide and determine the threshold values? For the calculation of threshold values either we use empirical methods or rely on expert opinions. In order to avoid such disputant techniques, we propose an algorithmic approach to solve the problem of rule inconsistency and redundant rules in this study.

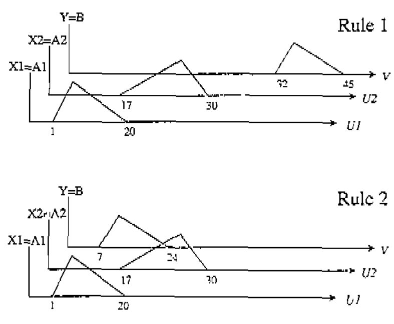

Fig. 1. An example of inconsistent fuzzy rules.

The commonality measure for rules in a rule base helps to detect and remove the inconsistent rules and the redundant rules, and create an optimized fuzzy rule base by deleting undesired fuzzy rules.

Before presenting the algorithm we will walk through a typical scenario. Let us assume fuzzy representation of a nonlinear function shown in Fig. 2. The rule base RB_1 comprises of five rules having one antecedent and one consequent as shown below:

R_1 : (X_1 is A_1) → (Y is B_1)
R_2 : (X_1 is A_2) → (Y is B_2)
R_3 : (X_1 is A_3) → (Y is B_3)
R_4 : (X_1 is A_4) → (Y is B_4)
R_5 : (X_1 is A_5) → (Y is B_5)

In Fig. 2, for the sake of simplicity we represent a fuzzy rule by a point in the rule space U×V, where U and V are the universe of discourses for the antecedent and consequent variables, respectively. Let us compute ϕ^1, the commonality measure of R_1 with respect to the other four rules. We have $\phi^1 = \phi^{12}+\phi^{13}+\phi^{14}+\phi^{15}$ where the individual commonality measures are computed as ϕ^{12}=0.6, ϕ^{13}=0.8, ϕ^{14}=0.7, and ϕ^{15}=0.1, and thus we get ϕ^1=2.2. Similar computations are done for the other rules and then we obtain ϕ^2=1.9, ϕ^3=2.5, ϕ^4=2.4, and ϕ^5 =0.83. Validating our intuition, we find from our computation that R_3 is closer to R_1, R_2, and R_4 where compared with R_5. Therefore, R_3 holds maximum commonality measures of R_1, R_2, and R_4. In fact, it appears to have more common information and should be treated as redundant information sources.

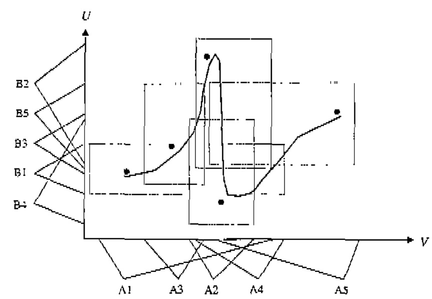

Fig 2. A nonlinear function modeled by 5 fuzzy rules.

The next question that arises, is it possible to delete it from the rule base without affecting the overall rule base performance? Before we make a decision to rule out R_3, we assign it as a most likely candidate for removal. But we make the final decision only after evaluating the effects of the rule base by temporarily blocking individual rules one at a time. The commonality measure of the rule base without using R_1 is

$$\phi_{RB_1-R_1} = \sum_{l=2}^{5} \sum_{k=l+1}^{5} \phi^{lk} = 5.5 \qquad (11)$$

Similarly, the commonality measures of the rule base by removing the other rules are given by:

$$\phi_{RB_1-R_2}=\sum_{l=1,l\neq 2}^{5}\sum_{k=l+1,k\neq 2}^{5}\phi^{lk}=6.05 \quad (12)$$

$$\phi_{RB_1-R_3}=\sum_{l=2,l\neq 3}^{5}\sum_{k=l+1,k\neq 3}^{5}\phi^{lk}=4.85 \quad (13)$$

$$\phi_{RB_1-R_4}=\sum_{l=2,l\neq 4}^{5}\sum_{k=l+1,k\neq 4}^{5}\phi^{lk}=8.15 \quad (14)$$

$$\phi_{RB_1-R_5}=\sum_{l=2,l\neq 5}^{5}\sum_{k=l+1,k\neq 5}^{5}\phi^{lk}=5.0 \quad (15)$$

Thus, we observe that by removing the most likely candidate R_3 the commonality of the rule base decreases most. And that's what we want to know which rule induces the maximum redundant information to the rule base. From our example we notice that R_3 contributes redundant information to the rule base, and is an undesired rule. We should remove it from our rule base RB_1. Therefore, our new rule base RB_2 consists of four rules, R_1, R_2, R_4, and R_5, as shown in Fig. 4.

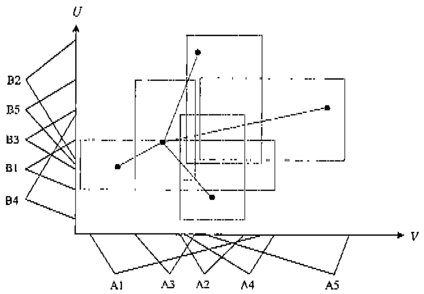

Fig 3. Measuring commonality measure from R_3.

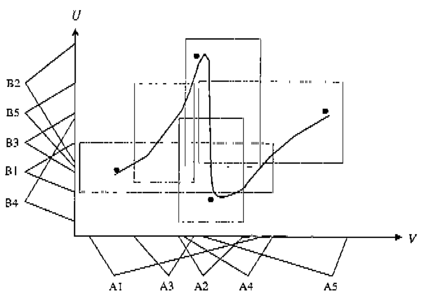

Fig. 4. Rules generated from *RBoptimizer*.

Similar to our previous steps we iterate over the computation of commonality measure of each of the rules. The commonality measure of R_1 with respect to the other three rules in RB_2 is computed by $\phi^1=\phi^{12}+\phi^{14}+\phi^{15}$. The individual commonality measures are given by $\phi^{12}=0.6$, $\phi^{14}=0.7$, and $\phi^{15}=0.1$ and thus we have $\phi^1=1.4$. Similar computations are done for the other rules. For those rules, we find $\phi^2=1.4$, $\phi^4=1.5$, $\phi^5=0.55$. We find that R_4 is the most likely candidate for removal. Then we follow the similar process of evaluating the rule base by depriving each of the rules temporarily to verify the chosen candidate. The commonality measure of the rule base RB_2 without R_1 is:

$$\phi_{RB_2-R_1}=2.1 \quad (16)$$

A similar computation to (12)-(15) provides the other commonality measures required:

$$\phi_{RB_2-R_2}=2.05 \quad (17)$$

$$\phi_{RB_2-R_4}=2.8 \quad (18)$$

$$\phi_{RB_2-R_5}=3.75 \quad (19)$$

However, in this step we observe that $\phi_{RB_2-R_2}$ has the minimum commonality measure, not $\phi_{RB_2-R_4}$. We stop removing the rules when the likely candidate can no longer be removed. Thus, in our working example we finally have a rule base with four rules R_1, R_2, R_4, and R_5.

The algorithm for removal of inconsistent and redundant fuzzy rules is shown below:

Procedure *RBoptimizer* (RuleBase RB)
begin
loop := **TRUE**;
while (loop == **TRUE**)
begin
1. Compute commonality measures for each individual rule: $\phi^l=\sum_l \phi^{lk}, \forall l\in\{1,\ldots,p\}$.
2. Find the rule that has the maximum commonality measure, let $\phi^i=Max(\phi^l)$, $\forall l\in\{1,\ldots,p\}$. We set R_i as the most likely candidate for removal from the rule base.
3. Remove each rule from RB and compute $\phi_{RB-R_l}=\sum_l\sum_k \phi^{lk}, \forall l\in\{1,\ldots,p\}$.
4. Find the minimum of ϕ_{RB-R_l}
5. **if** $(l\neq i)$ **then**
loop := **FALSE**;
else
Remove the rule R_l from the current rule base and update to a new rule base.
end
end

V. Conclusions and Future Work

Inconsistencies among rule sets are not desirable in any system that significantly relies on rule bases. This brief paper is a result of our preliminary study of fuzzy rule inconsistencies and anomalies that exist in fuzzy rule bases. Rule inconsistency issue in fuzzy rule bases needs further investigation to resolve this practical problem.

Here we have addressed the fuzzy rule inconsistency issue, and have shown how to optimize a rule base by removing inconsistent and redundant rules based on the newly proposed measures called Commonality measure. Commonality measure based approach can be treated as an alternative method of fuzzy rule base optimization. We are in a process of comparing our methodology of rule base optimization with other existing methods.

Among the other issues like performance measures of optimized rule bases, experimental verification, and further enhancement of this technique remains to be done. Usually performance of a rule base is assessed in terms of accuracy and the number of rules. We need to study how the proposed optimized rule bases perform with respect to the original rule bases.

Among other future works we would like to discuss the issue of optimality. However, optimality is quite a challenge, since we usually have more than one criterion such as accuracy, number of rules, etc to evaluate it. Objective functions are being evaluated and tested to understand this problem in a better way.

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