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Literature Survey on Genetic Algorithm Approach for Fuzzy Rule-Based System

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Abstract- Fuzzy-Rule Based Clustering (FRBC) is proposed, for automatically exploring potential clusters in dataset. This uses supervised classification approach to achieve the unsupervised cluster analysis. Fusion of clustering and fuzzy set theory is nothing but fuzzy clustering, which is appropriate to handle problems with imprecise boundaries of clusters. A fuzzy rule-based classification system is a special case of fuzzy modeling, in which the output of system is crisp and discrete. Fuzzy modeling provides high interpretability and allows working with imprecise data. To explore the clusters in the data patterns, FRBC appends some randomly generated auxiliary patterns to the problem space. It then uses the main data as one class and the auxiliary data as another class to enumerate the unsupervised clustering problem as a supervised classification one.

I. INTRODUCTION

Clustering is unsupervised approach where we do not need to provide training data. The task of separating different object in to groups is nothing but cluster, in which the objects in the same group are much more identical to each other than objects in other group. Ref.[2], one of the major problems in cluster analysis is the determination of the number of clusters in unlabeled data, which is a basic input for most clustering algorithms, which can be find using cluster validity function[7]. Ref. [10], synthesis between clustering and fuzzy set theory is fuzzy clustering, in which one object may belongs to number of clusters. Fuzzy clustering is useful in handling unclear boundaries of clusters. Ref. [9], fuzzy *c*-means clustering (FCM) is the most popular fuzzy clustering algorithm whose time requirement is high. It also suffers from the presence of noise and outliers and the difficulty to identify the initial partitions. A special case of fuzzy modeling is the fuzzy rule-based classification system, whose output is crisp and discrete. Ref.[3], then fuzzy rules are generated using SGERD" A steady state genetic algorithm for extracting fuzzy classification rules from data", whose product is best rule on the basic of that best rule process of clustering takes place.

Genetic algorithms (GAs) are search algorithms that provide a robust search capability in complex spaces hence fulfills an efficient and effective searching feature.

Ref. [3], E. G. Mansoori et al in SGERD, proposed method for extraction of fuzzy rule from given data set. This algorithm is generational and population-based, where its generations are finite and bounded to the problem dimension. Individual selection of this algorithm is serial, and only the best ones can survive. Each parent produces a finite number of offspring through reproduction. SGERD uses fitness function which is , based on a rule evaluation criterion, provides the best rules among all candidates.

Ref. [4] H. Ishibuchi and T. Yamamoto stated in comparison of heuristic criteria for fuzzy rule selection in classification problems, fuzzy rules are used for knowledge representation with high interpretability. Some heuristic criteria's are used for extraction of prespecified number of fuzzy rule .Genetic algorithm based rule selection criteria improves classification ability of extracted fuzzy rule. Ref. [4], there are seven different rule selection criteria viz. confidence, confidence with minimum support level, support with minimum confidence level, SLAVE (Structural Learning Algorithm in a Vague Environment) criteria and Castro criteria. Heuristic procedure is used here for obtaining good rule set.

In this paper, we present SGERD to generate fuzzy rules from a set of training data. The rest of this paper is organized as follows. In Section II, we briefly describe blueprint of membership function. In Section III, we present fuzzy rule generation methods. In Section IV, we present SGERD algorithm. The conclusion is discussed in Section V.

II. BLUEPRINT OF MEMBERSHIP FUNCTION

Fuzzy rules are simply IF-THEN rules, used for knowledge representation with high interpretability. For a pattern classification problem, Fuzzy IF–THEN rules include two clauses viz. antecedent and consequent. Antecedent clause includes conditions for the occurrence of the event; while consequent contain consequence of antecedent clause. Fig. 1 shows membership functions for four different values of *K*, where *L3*, *L*4 and L5 are the linguistic labels, which interprets linguistic values *small*, *medium*, and *large*, respectively.

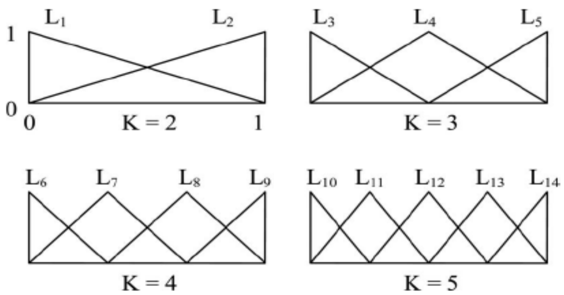

Fig. 1.Different partitioning of each input attributes [1].

For generating fuzzy rules we need to draw membership function for corresponding input data. The length of membership function is obtained using difference between maximum and minimum value of the attribute. Membership function rescaled each input attribute to unit interval [0, 1] by using linear transformation that preserves the distribution of training patterns. Then, partitioning the pattern into fuzzy subspaces took place where each subspace is identified by a fuzzy rule. By assigning linguistic values to each input attribute we can do partitioning. Generally, triangular membership functions are used for this purpose, as they are simpler and more human understandable with high interpretability [1].

When an input partitioning of pattern is given, then we can generate fuzzy rules for all combinations by considering all possible combinations of antecedent linguistic values. However, this is not easily handled as far as high dimensional problems are concern, as it generates numerous rules. For example, for a data set having n input attributes, K^n fuzzy rules might be generated.

This problem can be solved using some rule evaluation criteria to select a small subset of rules among all candidates [4].This approach simultaneously considers all membership functions in Fig. 1 for each attribute. That is, one of the 14 fuzzy sets can be used for each attribute when generating a candidate rule. In this case, for an n-dimensional problem, 14^n antecedent combinations should be considered. However, practically it is not possible to consider such a huge number of antecedent combinations when dealing with high-dimensional problems. Solution for this problem is presented in [6] by adding the fuzzy set *don't care* (with linguistic label *L*0) to each attribute.

Example1: Let us consider two data patterns x1 and x2.
If *x*1 is *small* and *x*2 is *small* then Class 1 ………………. (i)
If *x*1 is *small* and *x*2 is *large* then Class 2 ...…………….. (ii)
If *x*1 is *large* and *x*2 is *small* then Class 3 ……………… (iii)
If *x*1 is *large* and *x*2 is *large* then Class 4 ….…………..… (iv)

When fuzzy rule-based systems are used for two-dimensional problems, generated fuzzy rules [4] from above equations are shown in fig. 2.

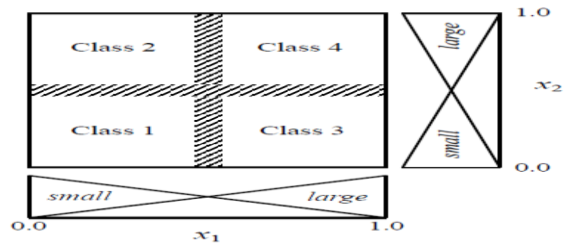

Fig 2. Four fuzzy rules in two-dimensional pattern [0, 1] × [0, 1].

III. GENERAL DESIGN OF FUZZY RULE-BASED CLASSIFIERS

Fuzzy IF–THEN rules for a pattern classification problem for n attributes can be written as follows [1]:

Rule *Rj*: IF *x*1 is *Aj*1 and . . . and *xn* is *Ajn*
THEN class *Cj*, for $j = 1, N$ (1)

Where X = [*x*1, *x*2, *xn*]
≡ n-dimensional pattern vector,
Aji ≡ Antecedent linguistic value of *Rj*,
Cj ≡ Consequent class,
N ≡ Number of fuzzy rules.

Generally, for an *M*-class problem with *m* labeled patterns *Xp* = [*xp* 1 , *xp* 2 , . . . , *xpn*],where $p = 1, \dots, m$, our task is to design the classifier to generate N fuzzy rules as in (1). Using training pattern in the corresponding fuzzy subspace consequent class *Cj* of the fuzzy rule *Rj in* (1) can be determined. The compatibility grade of the training pattern *Xp* is defined with the antecedent part of the rule, by the usage of the product operator as

$$\mu j(Xp) = \prod_{i=1}^{n} \mu ji(xpi) \qquad (2)$$

Where μji (.) is the membership function of the antecedent fuzzy set *Aji* .Using heuristic method which is based on confidence we select the consequent class of a rule [4]. This confidence is given as

$$conf(Aj \Rightarrow ClassT) = \frac{\sum_{Xp \in classT} \mu j(Xp)}{\sum_{p=1}^{m} \mu j(Xp)} \qquad (3)$$

Hence from (3), the consequent class *Cj* is determined using the maximum confidence, shown using (4).

$$Cj = \arg\max\{conf(Aj \Rightarrow classT) | T = 1, \dots, M\} \qquad (4)$$

Input partitioning of the pattern space is given, there are many approaches to generate fuzzy classification rules from data.

Using heuristic methods candidate rules can be evaluated easily [3]. Their basic criterion, which is a fuzzy version of the difference between the number of true positives and false positives, is specified as in (5).

$$f(Aj \Rightarrow classCj) = \sum_{Xp \in classCj} \mu j(XP) - \sum_{Xp \notin classCj} \mu j(Xp) \qquad (5)$$

Single winner rule is the most popular and simple reasoning method in fuzzy rule-based classifiers. Using this method, new pattern Xt = [xt 1, xt 2, xtn] is classified according to the consequent class of the winner rule Rw. In fact, the winner rule has the maximum compatibility grade with Xt among the fired rules. This can be stated as

$$\mu w(Xt) = \max\{\mu j(Xt), j = 1,2,\ldots,N\} \quad (6)$$

IV. FUZZY RULE-BASED CLUSTERING ALGORITHM

Our anticipated approach uses supervised classification approach to do the unsupervised cluster analysis by the addition of some auxiliary data patterns to the main data and usage of a fuzzy classifier to solve this new problem.

For extracting each cluster FRBC considers all unlabeled data pattern as main data pattern and label them as class 1.Then generation of random data pattern takes place which are uniformly distributed data patterns. This random data pattern can be treated as auxiliary data pattern.

For high dimensional problem, it is impossible to generate specific number of uniform pattern, so they are produced randomly and added to pattern space as a class 2 to form two-class problem. Auxiliary data generation is controlled by number of main data and their distribution.

For appropriately estimation of the number of auxiliary data pattern should be added, the summation of a within-cluster point to-point scatter matrix is used. This value for main data is defined

$$q = \sum_{i<j} d(Xj, Xi) \quad (7)$$

Where Xi is one of the mM main data patterns, and d (.,.) is a distance metric, which is usually the Euclidean norm. Similarly, for auxiliary data $\{X'_{i,\,i}=1, mA\}$

$$q' = \sum_{i<j} d(X'i, X'j) \quad (8)$$

Auxiliary random patterns are added incrementally using q and q' until q exceeds q'. In this regard, the distribution of main data patterns influences the size of auxiliary instances.

After the preparation of the two-class problem, the FRBC make use of SGERD for a fuzzy rule generation to solve two-class problem. Then rule evaluation measures can be applied for the rule R_j.

$$f(Aj \Rightarrow class1) = \frac{\sum_{Xp\in class1} \overline{\mu}j(Xp) - \sum_{Xp\in class2} \overline{\mu}j(X'p)}{\eta' j} \quad (9)$$

Where $\eta' j =$ Number of auxiliary patterns that are covered by the rule Rj

After generation of the fuzzy rules, the FRBC sets best rule as the initial members of the first cluster and removes them from the problem space to not be reconsidered for other clusters.

In this manner FRBC explore all potential clusters with assignment of distinct class labels to the consequent of fuzzy rules that represent the explored clusters [8]. It then uses the fuzzy rules simultaneously to classify the main data patterns and, therefore, identify the clusters' boundaries. Since the FRBC uses the single winner-rule reasoning method, it selects fuzzy rule with highest compatibility grade as in (6).To increase the clustering accuracy [5], centroids can be calculated as in (10)

$$Cj = \frac{\sum_{Xp\in Gj} \mu j(Xp) \times Xp}{\sum_{Xp\in Gj} \mu j(XP)} \quad (10)$$

Algorithm: Fuzzy rule-based clustering algorithm.
Inputs: mI unlabeled data patterns and threshold τ .
Outputs: The number of clusters J and their members that are identified by J fuzzy classification rules.

1. Name the unlabeled patterns $\{Xp , p = 1, \ldots , mI \}$ of the problem as the main data.
2. Let j = 1 (j: the cluster number).
3. Let $mM = mI$ (mM : number of main data (non clustered) patterns).
4. Generate some uniformly random patterns and append them incrementally to the main data patterns until q_ in (8) exceeds q in (7) (call these added patterns $\{X'p, p =1, mA\}$ as auxiliary data).
5. Label mM main data patterns as Class 1 and mA auxiliary data as Class 2.
6. By the usage of SGERD with the criterion in (9), generate fuzzy rules to classify this two-class problem (with $mM + mA$ data patterns).
7. Among the rules that are generated for Class 1, choose the best one and name it Rj.
8. **If** e $(Rj) < \tau$ **goto** Step 12.
9. Set aside the main data patterns in the fuzzy subspace of Rj as the initial members of cluster Gj.
10. Remove the members of Gj from the problem space, and let $mM = mM - |Gj|$.
11. Let $j = j + 1$, then **goto** Step 4.
12. Let $J = j - 1$ as the number of explored clusters and $R1$, RJ as their representing fuzzy rules, where Rj identifies cluster Gj.
13. Replace the consequent of the rule Rj with j (for j =1,. . , J) so that the fuzzy rule base, which represents clusters $\{G1, GJ\}$, would be $\{R1, \ldots , RJ \}$ with the consequents $\{1, \ldots , J\}$.
14. By the usage of the fuzzy rule base, classify the mI unlabeled patterns to identify the actual members of J *explored* clusters.
15. Compute the centroid of J clusters from (10).

16. Regroup the *mI* unlabeled patterns according to the nearest centroid of *J* clusters.
17. **Stop**.

V. FUZZY RULE GENERATION METHOD

Method used in generating fuzzy rules is SGERD, which is discussed bellow.

A. Steady state genetic algorithm for extracting fuzzy classification rules from data:-

SGERD generates a prespecified number of *Q* rules per class ($R = M \times Q$ rules in total at most). Input for this algorithm is labeled pattern and projected output is fuzzy rules.

Algorithm: SGERD.

Inputs: *m* labeled patterns of an *n*-dimensional *M*-class problem and *Q*.

Outputs: Possibly $R = M \times Q$ fuzzy classification rules.

1. $i = 1$ (*i:* generation number).
2. Generate all fuzzy rules having only one active antecedent variable (at most $C = 14 \times n$ candidate rules would be generated).
3. Determine the consequent class of each candidate rule using (4).
4. Divide the candidate rules into *M* groups according to their consequent class.
5. Rank, in descending order of their fitness values, the Candidate rules in each group.
6. Choose the best *Q* rules from each class (i.e., possibly $R = M \times Q$ rules in total) as the population in the i^{th} generation. In the first generation only, choose the second best *R* rules as the auxiliary population and put away for mutation.
7. Increment *i*, **if** $i > n$, **goto** step 11.
8. Use all individuals in the previous generation (i.e., *R* rules) as parents and do reproduction (i.e., crossover, mutation, or elitism) on them. That is, for each parent rule, generate as offspring all fuzzy rules having one more active antecedent variable than its parent, provided each new offspring is fitter than its parent. In this case, the number of offspring will totally be $R \times 14$ at most.
9. **If** no offspring fitter than the parents is produced in step (8), **goto** step 11.
10. Consider both parents and offspring in step 8 as Candidate rules (at most $C = R + R \times 14$ rules in total) and **goto** step 3.
11. Use $R = M \times Q$ rules (obtained in step 6 for the i^{th} generation) as the final population and **stop**. The actual length of these rules is *i* or less.

As mentioned before, the rule selection scheme in SGERD only considers the evaluation measure of each rule to select the best ones through competition.

V.CONCLUSSION

In this paper, we proposed FRBC is a novel fuzzy rule-based clustering algorithm to automatically explore the potential clusters in the datasets. It looks at the clustering issue as a classification problem by the addition of some auxiliary data patterns to the main data and then generation of some fuzzy rules to classify the new pattern space. The generated fuzzy rules, which represent the clusters, are human understandable with acceptable accuracy. SGERD is a steady-state genetic algorithm to extract fuzzy classification rule from data. Best rule is generated in SGRED.

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