A Classifier Ensemble Method for Fuzzy Classifiers

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Abstract. In this paper, a classifier ensemble method based on fuzzy integral for fuzzy classifiers is proposed. The object of this method is to reduce subjective factor in building a fuzzy classifier, and to improve the classification recognition rate and stability for classification system. For this object, a method of determining fuzzy integral density based on membership matrix is proposed, and the classifier ensemble algorithm based on fuzzy integral is introduced. The method of selecting classifier sets is also presented. The proposed method is evaluated by the comparison of experiments with standard data sets and the existed classifier ensemble methods.

1 Introduction

Fuzzy Classification is an important application of Fuzzy Set. Fuzzy classification rule is widely considered a well-suited representation of classification knowledge, and is readable and interpretable. Fuzzy classification has been widely applied in many fields, such as image processing, words recognition, voice recognition etc.

The auto-generation of fuzzy partition and fuzzy classification rules is a key problem for the fuzzy classification research, along with expressions and adjustments of classification rules and the improvement of the classification recognition rate. Although a single fuzzy classifier has implemented the auto-generation of fuzzy Partition and fuzzy classification rules with good classification performance to some extent, it needs to select the type of membership function and parameters and to take some time to learn these parameters for a good classifier. This paper proposed a classifier ensemble method with fuzzy integral density[11] which can generate fuzzy classification rules automatically and can decrease subjective factors during training classifier.And the method of measuring generalization difference(GD) for classifier sets is also introduced. The proposed methods are evaluated by the experiments.

2 Related Works

(1) Fuzzy Classifier Rules

The typical fuzzy classification IF-THEN rules[1-2] have the form as Eq.(1).

$$\begin{aligned} &R_k : IF \quad x_1 \quad is \quad A_{1,i(1,k)} \quad AND \quad ...A_{j,i(j,k)} \quad ... \quad AND \quad x_n \quad is \quad A_{n,i(n,k)} \\ &THEN \quad g_{k,1} = z_{k,1} \quad AND...AND \quad g_{k,M} = z_{k,M} \end{aligned} \quad . \tag{1}$$

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In Eq.(1), $x=[x_1,\ldots,x_n]^T \in R^n$ is input pattern, x_i is feature property, $\Omega=\{C_1,\ldots, C_m,\ldots, C_M\}$ is the set of class label. FSN_j is the number of linguistic label of the j-th feature, $A_{j,i}$ is the i-th fuzzy set in x_j feature axis (i =1,…, FSN_j, j =1,…,n), $g_{k,m}$ is the discriminant function of C_m related with rule R_k, suffix i(j,k) is the function of fuzzy set serial number describing x_j in rule R_k, $z_{k,m} \in R$ can be seen as the support degree of C_m(m=1,2,…,M) for R_k rule. $z_{k,m} \in [0,1]$, $[z_{k,1},\ldots,z_{k,M}]^T$ is soft classification output.

(2) Fuzzy Integral

Definition 1. Suppose g_λ is Fuzzy measure[11], and has property as follows.

If $A, B \subset X \quad and \quad A \cap B = \Phi$, then Eq.(2)

$$g_\lambda(A \cup B) = g_\lambda(A) + g_\lambda(B) + \lambda g_\lambda(A) g_\lambda(B) \qquad \lambda > -1. \tag{2}$$

So, g_λ is called as λ fuzzy measure. g_λ has the following properties:

Suppose $X=\{x_1,\ldots,x_n\}$ is a finite set, and $g^i=g_\lambda(\{x_i\})$, then $\{g^1,\ldots, g^n\}$ is called as g_λ fuzzy density function. So, for arbitrary subset of X, $A=\{x_{i_1},\cdots,x_{i_m}\} \subseteq X$, the measure value of g_λ can be got from fuzzy density function, as Eq.(3)

$$\begin{aligned} g_\lambda(A) &= \sum_{j=1}^{m} g^{i_j} + \lambda \sum_{j=1}^{m-1} \sum_{k=j+1}^{m} g^{i_j} g^{i_k} + \cdots + \lambda^{m-1} g^{i_m} \cdots g^{i} \\ &= \left[\prod_{x_i \in A} (1+\lambda g^i) - 1 \right] \Big/ \lambda, \qquad \lambda \neq 0 \end{aligned} \tag{3}$$

λ is calculated according to Eq.(4).

$$X = \bigcup_{i=1}^{n} \{x_i\}, \quad g(X) = 1 \quad \text{i.e.,}\ \lambda + 1 = \prod_{i=1}^{n} (1+\lambda g^i) . \tag{4}$$

For a set $\{g^i\}(0<g^i< 1)$, the above equation has a solution satisfying the following form:$\lambda \in (-1,+\infty)$, and $\lambda \neq 0$.

So,if fuzzy density g^i(i=1,2,…,n) is known, g_λ can be constructed. For information integral, the description of fuzzy density g^i can be as the important degree of final decision from information source x_i. The fuzzy measure of arbitrary set A expresses the important degree of final decision for A.

Definition 2. Assume (X, Ψ) is a measure space, h: X→[0,1] is a measure function, then the fuzzy integral of h about fuzzy measure g_λ in $A(A \subseteq X)$ is Eq.(5).

$$\int_A h(x) \circ g_\lambda(\cdot) = \sup_{\alpha \in [0,1]} [\min(\alpha, g_\lambda(A \cap F_\alpha))] \tag{5}$$

Where, $F_\alpha = \{x \in A \mid h(x) \geq \alpha\}$.

If X is a finite set, Fuzzy Integral[3] can be calculated. Suppose $X=\{x_1,x_2,\ldots,x_n\}$ is a finite set, h:X→[0,1] is a function, and $h(x_1) \geq h(x_2) \geq \ldots \geq h(x_n)$, then the value of fuzzy integral h(x) for fuzzy measure g_λ can be computed using Eq.(6).

$$\int_X \mathrm{h(x)} \circ \mathrm{g}_\lambda = \max_{i=1}^{n} [\min(h(x_i), g_\lambda(A_i))] . \tag{6}$$

Where, $A_i=\{x_1,\ldots,x_i\}$, and $g_\lambda(A_i)$ can be determined by Eq.(7).

$$\begin{aligned} &g_\lambda(A_1)=g_\lambda(\{x_1\})=g^1 \\ &g_\lambda(A_i)=g^i+g_\lambda(A_{i-1})+\lambda g^i g_\lambda(A_{i-1}), 1<i\le n \end{aligned} . \tag{7}$$

(3)Three Types of Fuzzy Classification Model

The propposed ensemble method uses three types of fuzzy classification models[12] which were proposed in our early research.

Model I. Fuzzy Classification Model Based on Fuzzy Kernel Hypersphere Perception (FCMBFKHP). For this model, firstly the input patterns in the initial input space are mapped to high dimensional feature space by selecting a suitable kernel function. In the feature space, the hypersphere which covers all training patterns of the class is founded for every class by the algorithm of FKHP. A hypersphere is regarded as a fuzzy partition and a IF-THEN rule is created for a fuzzy partition. A hyper-cone membership function is defined with regarding the center and radius as parameters. Fuzzy classification rule is as Eq.(8).

$$R_m:\ IF\ \Phi(x)\ is\ around\ C_m\ \ THEN\ x\in C_m\ with\ CF=\alpha_m\ . \tag{8}$$

Where, R_m denotes labels of rule, created by the m-th class, CF denotes the degree of pattern $\Phi(x)$ belonged to this rule, $\alpha_m\in[0,1]$,Φ is a kernel function.

Model II. Fuzzy Classification Model Based on Evolving Kernel Clustering (FCMBEKC). For this model, firstly the patterns in the initial input space are mapped to high dimensional feature space by selecting a suitable kernel function. In the feature space, several hyperspheres are got by clustering for each class training patterns by the algorithm of EKC(Evolving Kernel Clustering). A hypersphere is regarded as a cluster which corresponds to a fuzzy partition that creates a IF-THEN rule. A hyper-ellipse membership function is defined with the center of each cluster as parameters. Fuzzy Classification rule is as Eq.(9).

$$R_{mj}:\ IF\ \Phi(x)\ is\ around\ C_{mj}\ \ THEN\ x\in C_m\ with\ CF=\alpha_{mj}\,. \tag{9}$$

Where, R_{mj} denotes labels of rule, created by the j-th cluster of the m-th class, CF denotes the degree of pattern $\Phi(x)$ belonged to this rule, Φ is a kernel function.

Model III. Fuzzy Classification Model Based on Support Vector Machine (FCMBSVM). In the initial stage of the model construction, the center around of each training pattern is regarded as a fuzzy partition.Each training pattern corresponds to a fuzzy partition which creates a IF-THEN rule. Kernel function is constructed by selecting suitable membership function. The parameters of SVM and rules are gained using SVM learning method. This model can automatically generate fuzzy partition and fuzzy classification rule. Classification rule is as Eq.(10).

$$\begin{aligned} &R_k: IF\quad x_1\quad is\quad A_{1,k}\quad AND\quad \ldots A_{j,k}\quad \ldots\quad AND\quad x_n\quad is\quad A_{n,k} \\ &THEN\quad Class\quad is\quad C_m\quad with\quad \alpha_{k,m} \end{aligned} . \tag{10}$$

Where, R_k is the k-th rule(k=1,2,…,l) , $A_{j,k}$ is fuzzy subset from the projection on the j-th axis (feature) using the i-th training pattern as center, is also the subset of the k-th rule in the j-th axis. $C_m \in \{-1,1\}$(m=1,2) represents the class, $\alpha_{k,m}$(k=1,2,…,l) can be seen as the support degree of class C_m for rule R_k.

3 The Method of Classifier Ensemble Based on Fuzzy Integral

During classifier ensemble with Fuzzy Integral, there are two factors for a pattern evaluation. One is the individual classifier evaluation. In this paper,this evaluation is membership degree, i.e. measure function h in Fuzzy Integral theory. The other is dependability degree of each classifier, i.e. fuzzy integral density g. These factors can be expressed by classification precision for each class.

3.1 The Generation of Individual Classifier

The most important technique in individual classifier generation[10] is Boosting[4] and Bagging (Bootstrap Aggregating) algorithm[5] . In our research, the following aspects are considered.

① According to different classification models,in 2 section, three classification models are introduced,FCMBFKHP, FCMBEKC and FCMBSVM. So, individual classifiers can be generated from the three models.

② By selecting different types of kernel functions and parameters, in the proposed models, the initial model spaces are mapped into high dimensional feature spaces with kernel function. So, different individual classifier can be got by selecting different kernel functions and parameters, such as radial basis kernel function, polynomial kernel function. And different individuals can be created from the different parameters, such as δ parameter of radial basis kernel function, penalty parameter C of support vector machine etc.

3.2 Selection of Classifier Sets

After selection of individual classifier, an important question in classifier ensemble system is how to construct classifier sets in order to decrease the relativity of classifiers. A common method is firstly constructing N individual classifiers, then a classifier set is built with K(K<N) classifiers selected, and then several classifier sets and their relativity are got through repetition by defining the method of computing total relativity of a group of individual classifiers. At last, a criterion of selecting classifier set is defined to select classifier sets for classifier ensemble system.

Turner and Gosh [6] point out that improvement of multi-classifier ensemble performance depends on the speciality that wrong decision patterns for each classifier. That is, the less the patterns in which each classifier makes wrong decision at the same time, the higher the recognition performance.So according to this idea and the different influences on ensemble decision by different number of classifiers making wrong decision, a measuring generalization difference method (GD)for individual classifiers is introduced as the criterion of selecting classifier set. This method is similarity to the idea of generalization difference among neural network ensemble individuals proposed by Partridge [7-8].

First, define the wrong probability of an arbitrary individual classifier as Eq.(11).

Definition 3. $p(\text{arbitrary misclassification}) =$

$$\sum_{k=1}^{K} p\left(\text{selected misclassifications} \middle| \text{k misclassifications}\right) \times p\left(\text{k misclassifications}\right)$$

$$= \sum_{k=1}^{K} \frac{k}{K} \times p_k \tag{11}$$

(p_k is the probability that k classifiers are misclassifications at the same time)

The following defines the wrong probability of two arbitrary classifier on randomly selecting test patterns as Eq.(12).

Definition 4. $p(\text{two arbitrary misclassifications}) =$

$$\sum_{k=2}^{K} p\left(\text{selected misclassifications} \middle| \text{k misclassifications}\right) \times \text{p}\left(\text{k misclassifications}\right)$$

$$= \sum_{k=2}^{K} \frac{k}{K} \frac{k-1}{K-1} p_k \tag{12}$$

(p_k is the probability that k classifiers are misclassifications at the same time)

A misclassification table can be built for several classifiers. p (one misclassification) is the wrong probability of an arbitrary classifier selected from K classifiers on test patterns, while p (two misclassifications) is the wrong probability of two arbitrary classifiers on test set. Like this generalization, the generalization difference of different individual classifier sets can be determined. The following defines a calculation method for generalization difference(GD) of classification set.

Definition 5. GD of classifier set in some test set is defined as Eq.(13).

$$GD = \frac{p(\text{one misclassification}) - p(\text{two misclassifications at the same time})}{p(\text{one misclassification})} \tag{13}$$

According to Definition 5, the classifier set with the max GD is selected to ensemble.

3.3 Determination of Fuzzy Integral Density Based on Membership Degree Matrix

The following is the way to determine fuzzy integral density, firstly, membership degree matrix (MDM) is got from the given test set, then, using membership degree matrix, confusion matrix (CM) is got, which can be used to calculate fuzzy integral density g.

Supposes $C_m(m \in \Lambda=\{1,...,M\})$ denotes M different classes , $e_k(k=1,...,K)$ denotes K different classifiers respectively, then the output of classifier e_k for pattern x can be expressed by $\mu_k(x)=(\mu_{k1},\ldots, \mu_{km},\ldots, \mu_{kM})$, where $0 \le \mu_{km} \le 1$ means membership degree of classifier e_k for x, and then select the label of the maximal μ_{km} as the class label of pattern x, thus pattern x belongs to the corresponding class.

Definition 6. $MDM(x) = [\mu_1(\mathrm{x})^T, \mu_2(\mathrm{x})^T, ..., \mu_K(\mathrm{x})^T]^T = \begin{bmatrix} \mu_{11} & \cdots & \mu_{1\mathrm{M}} \\ \vdots & \mu_{km} & \vdots \\ \mu_{K1} & \cdots & \mu_{K\mathrm{M}} \end{bmatrix}$ is called membership degree matrix of pattern x for multi classifiers $\{e_k, k=1,\ldots,K\}$.

Definition 7. For pattern set S=$\{x_i,\ i=1,\ldots,L\}$, MDM(S)=[MDM (x_1),…, MDM (x_i),…, MDM (x_L)] is membership degree matrix of pattern set S with multi classifiers $e_k(k=1,2,\ldots,K)$.

Membership degree matrix includes all classification results of each pattern in pattern or pattern set, which can be used to statistic and analyze classification precision, relativity of classes and so on. The following will analyze how to get confusion matrix from membership degree function.

Calculation of Confusion Matrix(CM),CM for e_k is Eq.(14).

$$\mathrm{CM}_k = \begin{bmatrix} r_{11}^{(k)} & r_{12}^{(k)} \cdots & & r_{1\mathrm{M}}^{(k)} \\ r_{21}^{(k)} & \ddots & & \vdots \\ & & r_{ml}^{(k)} & \vdots \\ r_{\mathrm{M}1}^{(k)} & \cdots & \cdots & r_{\mathrm{MM}}^{(k)} \end{bmatrix}. \tag{14}$$

Where, $r_{ml}^{(k)}$ is the probability that $\mathrm{e_k}$ judges the pattern belonging to $\mathrm{C_m}$ as C_l. CM can be calculated by MDM, and MDM of pattern set S of multi-classifier $\mathrm{e_k}$(k =1,2,..., K) is MDM(S)=[MDM $(\mathrm{x_1})$,…, MDM $(\mathrm{x_i})$,…, MDM $(\mathrm{x_L})$].

The k-th row of MDM(S) includes the classification output of all patterns of pattern set S with classifier e_k, CM of pattern set S with classifier e_k can be got with statisticing these cases.

The algorithm of calculating CM of classifier e_k is as follows.

Algorithm 1: Calculating CM of classifier e_k
Input: Pattern set S and corresponding MDM(S)
Output: CM of classifier e_k
Step1: Initialize R_k=M×M matrix, and let R_k=0.
Step2: Select x from pattern set S, determine its real class label (the class of training patterns or test patterns is given), assume it is m, the classification output $\mu=[\mu_{\mathrm{k}1},..., \mu_{\mathrm{km}}, ..., \mu_{\mathrm{kM}}]$of x is obtained from MDM(S) with classifier e_k, and add μ to row m-th of matrix R_k, and remove pattern x from S.
Step3: Judge S whether is null or not, if not null, the algorithm goes to Step1, else,go to **Step4.**
Step4: Normalize each row of matrix R_k with Eq.(15).

$$r_{ml} = R_k(m,l) \Big/ \sum_{q=1}^{M} R_k(m,q) \quad \text{where, } l=1,2,\ldots,\mathrm{M}\,. \tag{15}$$

Step5: Output confusion matrix R_k of classifier e_k.

Confusion matrix $R_k(k=1,2,\ldots,K)$ corresponding to other classifiers can be got, according to the above algorithm.Belief degree of classifier e_k as fuzzy integral density g^k can be got by Eq.(16) with confusion matrix.

$$g^k = \sum_{m=1}^{M} r_{mm}^{(k)} \Big/ \sum_{m=1}^{M}\sum_{l=1}^{M} r_{ml}^{(k)} . \tag{16}$$

3.4 Classifier Ensemble Method

For a given multi-classifier ensemble question, individual classifier is e_k, k=1,2,...,K, K is the number of classifiers, $\Omega=\{C_1,C_2,\ldots,C_M\}$ is class label set, M is number of classes, μ^k_m, $m=1,2,\ldots,M$ represents output of each individual classifier. For fuzzy integral, μ^k_m is the evaluation of classifier e_k for input pattern belonging to the *m-th* class, that is h_k. The performance of the current classifier shows the evaluation reliability, i.e. fuzzy integral density g^k. The method of calculating h_k and g^k has been introduced before.

Suppose τ: $\{\mu_1, \mu_2,\ldots, \mu_K\}$ is a finite set, $h:\tau\rightarrow[0,1]$ is a function, and $h(\mu_1)\geq h(\mu_2)\ldots\geq h(\mu_K)$, fuzzy integral is Eq.(17) according to Eq.(6).

$$FI = \max_{k=1}^{K}\left[\min\left(h(\mu_k), g_\lambda(A_k)\right)\right]. \tag{17}$$

Where, $A_k=\{\mu_1, \mu_2,\ldots, {}_{ik}\}$.

g_λ can be calculated with Eq.(7).

$$\begin{aligned} & g_\lambda(A_1) = g_\lambda(\{\mu_1\}) = g^1 \\ & g_\lambda(A_k) = g^k + g_\lambda(A_{k-1}) + \lambda g^k g_\lambda(A_{k-1}),\ \ 1 < k \leq K \end{aligned} . \tag{18}$$

Where, λ is calculated by Eq.(4).

$$\lambda + 1 = \prod_{k=1}^{K}(1+\lambda g^k) \qquad \text{Where, } \lambda\in(-1,+\infty)\text{,and } \lambda\neq 0.$$

Fuzzy integral of a input pattern x for a certain class can be got with Eq.(17), and fuzzy integral of this pattern for other classes can be calculated by the same way. If $FI_m(x)(m=1,2,\ldots,M)$ is fuzzy integral of input pattern x for each class, the decision model of multi-classifier ensemble system is as follows.

$$\text{Class}(x) = \arg\max_{m=1}^{\text{M}} FI_m(x). \tag{19}$$

The classifier ensemble algorithm is as follows.

Algorithm 2: Classifier Ensemble Algorithm
Input: pattern *x;* **Output:** class of *x*

Step1: For input pattern x, each individual classifier outputs the membership degree of x corresponding to each class.

Step2: For each class C_m, each classifier e_k calculates $h_m(\mu_k)$ and $g_\lambda(\mu_k)$, and fuzzy integral FI_m corresponding to C_m.

Step3: Judge the class for the pattern x with Eq.(19).

4 Analysis of Experiment Results

Wine data set and waveform data set are adopted for the experiment analysis, which come from UCI machine learning database[9]. wine data set has 13 features, the number of classes is 3, the number of training patterns is 118, and the number of test pattern is 60. Waveform data set has 21 features, number of classes m=3, training pattern 300, and test pattern 4700.

Individual classifier can be generated with fuzzy classification model introduced in section 2. Each model creates 10 classifiers with the strategy of selecting different kernel functions and parameters, and different membership functions and parameters.

So, the total number of individual classifiers is 30, which means there are 30 individual classifiers for selection. Each classifier set includes 6 individual classifiers to ensemble for constructing pattern classification system, which is selected by its generalization difference (GD). Wine data set is to train and test 30 individual classifiers, and randomly select 6 classifiers to compose an ensemble classifier. The recognition rate is got by the method of classifier ensemble based on fuzzy integral with test pattern testing. Calculating GD of individual classifier in ensemble classifier, the relationship of the recognition rate and generalization difference of classifier sets is got as Fig.1(some points are got rid off in convenient to observe).

In Fig.1, the whole trend is that system recognition rate improves with GD increasing. So, the method based on GD for selection classifier is feasible.

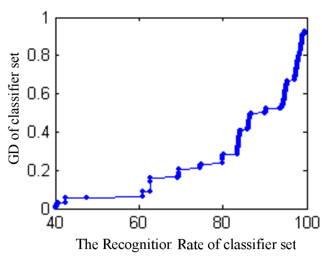

Fig. 1. Relationship of the recognition rate and generalization difference of classifier sets

Table 1. Comparison of recognition rate between the system of classifier ensemble and individual classifier

Classifier	wine (%)	waveform (%)
Classifier 1	91.67	74.65
Classifier 2	93.33	72.82
Classifier 3	90.00	80.0
Classifier 4	808.33	82.49
Classifier 5	95.00	79.1
Classifier 6	93.33	83.75
Classifier ensemble system	96.67	85.5

Table 2. Comparison of recognition rate between the proposed method and the others classifier ensemble methods

Ensemble method		Wine (%)	Waveform (%)
Max	means	93.85	84.83
	Bayesian	95.21	86.02
	vote	94.58	85.73
	proposed method	96.66	86.31
Average	means	93.25	83.39
	Bayesian	94.92	84.89
	vote	94.19	84.10
	proposed method	95.50	85.5

After selecting individual classifier, the performance of classifier system is analyzed though experiment which is constructed by multi-classifier ensemble. The comparison is done in two aspects, one is the recognition rate of classifier ensemble system and that average of individual classifier, the other is recognition rate between the proposed method and others classifier ensemble methods.

The experiment data set is also wine data set and waveform data set. Table 1 is comparison of recognition rate between the system of classifier ensemble and individual classifier. Table 2 is comparison of recognition rate between the proposed method and the others classifier ensemble methods.

From the experiment, the recognition rate of the classification system based on fuzzy integral classifier ensemble is obviously higher than the average recognition rate of individual classifier. So, how to determine parameters in individual classifier is solved by multi-classifier ensemble method.

5 Conclusions

This paper proposes the method of multi-classifier ensemble based on fuzzy integral and introduces the method of getting fuzzy integral density with membership degree matrix, the method of selecting individual classifier with GD of classifier set, and the algorithm of classifier ensemble based on fuzzy integral. We validate the efficiency of these methods and the performance of the classifier ensemble system with typical data set. The experiment shows it obviously improves the performance of the classification system based on classifier ensemble. This paper suggests a method how to select the parameters and optimize the performance for a single fuzzy classifier.

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