Performance Evaluation of Incremental Fuzzy Rule-Based Classifiers

Tomoharu Nakashima, Takeshi Sumitani, and Andrzej Bargiela

Abstract The adaptability of incremental fuzzy rule-based classifiers are investigated in this paper. The incremental fuzzy rule-based classifier is an extended version of fuzzy rule-based classification systems so that it adapts itself to a dynamic environment. It is assumed in this paper that only a small number of training patterns are available at a time and the classification boundaries change over time. Three incremental methods are considered in the fuzzy rule-based classifiers where the confidence factor of fuzzy if-then rules is modified in three different ways. The first method considers all training patterns that are made available during the course of pattern classification process. The other two discounts the weight of previously available training patterns. As a measure of classification performance, this paper examines the grid-based sampling from the entire pattern space. A series of computational experiments were conducted for a two-dimensional dynamic problem. The experimental results show the effectiveness of the weight-discounting in the incremental update of the fuzzy if-then rules.

1 Introduction

Fuzzy systems based on fuzzy if-then rules have been researched in various fields such as control [1], classification and modeling [2]. A fuzzy rule-based classifier is

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Tomoharu Nakashima
Graduate School of Engineering, Osaka Prefecture University, Gakuen-cho 1-1, Naka-ku, Sakai, Osaka 599-8531, Japan, e-mail: nakashi@cs.osakafu-u.ac.jp

Takeshi Sumitani
Graduate School of Engineering, Osaka Prefecture University, Gakuen-cho 1-1, Naka-ku, Sakai, Osaka 599-8531, Japan e-mail: takeshi.sumitani@ci.cs.osakafu-u.ac.jp

Andrzej Bargiela
University of Nottingham, Jubilee Campus, Wollaton Road, Nottingham NG8 1BB, U.K. e-mail: andrzej.bargiela@nottingham.ac.uk

composed of a set of fuzzy if-then rules. Fuzzy if-then rules are generated from a set of given training patterns. Advantages of fuzzy classifiers are mainly two-folds: First, the classification behavior can be easily understood by human users. This can be done by carefully checking the fuzzy if-then rules in the fuzzy classifier because fuzzy if-then rules are inherently expressed in linguistic forms. Another advantage is nonlinearity in classification. It is well known that non-fuzzy rule-based classifiers are difficult to perform non-linear classification because classification boundaries are always parallel to attribute axes in most cases. The nonlinearity of fuzzy classification leads to high generalization ability of fuzzy rule-based classifiers while its classification behavior is linguistically understood.

A fuzzy rule-based classifier in this paper consists of a set of fuzzy if-then rules. The number of fuzzy if-then rules is determined by the dimensionality of the classification problem and the number of fuzzy partitions used for each attribute. A fuzzy if-then rules is generated by calculating the compatibility of training patterns with its antecedent part for each class. The calculated compatibilities are summed up to finally determine the consequent class of the corresponding fuzzy if-then rule. An unseen pattern is classified by the fuzzy rule-based classifier (i.e. a set of generated fuzzy if-then rules) using a fuzzy inference process.

In general, as the amount of information keeps growing due to the development of high-performance computers and high-capacity memories, it is difficult for any information systems to efficiently and effectively process a huge amount of data at a time. This is because it takes intractably long time to retrieve whole data and it is not possible to handle the intractably huge amount of data by just one information system. Also, it is possible that training patterns are generated over time and the designers of information systems have to handle the dynamically available patterns in a manner of streaming process. This paper focuses on the latter case in the construction process of fuzzy rule-based classifiers. In order to tackle with such streaming data, fuzzy rule-based classifiers need to adapt themselves to newly available training patterns. In this paper, incrementally constructing methods are proposed for fuzzy rule-based classifiers. A series of computational experiments are conducted in order to examine the generalization ability of the constructed fuzzy rule-based classifiers by the proposed methods for a two-dimensional incremental pattern classification problem.

2 Incremental Pattern Classification Problems

The incremental pattern classification problem in this paper is defined as the classification task that involves an incremental process of obtaining training patterns. That is, the complete set of training patterns cannot be obtained beforehand. Instead, only a small number of training pattens are made available at a particular time step. It is also assumed that classification of new patterns should be always prepared at any time during the course of the incremental process. Thus, the classifier should be constructed immediately after the training patterns are available so that unknown patterns should be classified with the constructed classifier.

Let us denote the available training patterns at the time step t as xp, p = 1, 2, ... , in^t, where m^t is the number of training patterns that become available at time t. At each time step a classifier must be constructed or modified based on the previous one using xp, $p = 1, 2, \ldots, m^t$.

3 Fuzzy Rule-Based Classifier

In this paper, a fuzzy rule-based classifier proposed in [2] is used. It should be noted that the idea of the classification confidence can be applied to any forms of fuzzy classifiers if they are rule-based systems. A detailed overview of the system is given in [2] . In this section, only fuzzy if-then rule is described.

In a pattern classification problem with n dimensionality and M classes, we suppose that m labeled patterns, $x_p = \{x_pi, x_p2, \cdots, x_{pn}\}$, $p = 1, 2, \cdots, m$, are given as training patterns. We also assume that without loss of generality, each attribute of x_p is normalized to a unit interval [0, 1]. From the training patterns we generate fuzzy if-then rules of the following type:

$$R_q\text{: If } xi \text{ is } A_qi \text{ and } \cdots \text{ and } x_n \text{ is } A_{qn} \text{ then Class } C_q \text{ with } CF_q, \quad q = 1, 2, \cdots, N, \tag{1}$$

where R_q is the label of the q-th fuzzy if-then rule, $A_q = (A_qi, \cdots, A_{qn})$ represents a set of antecedent fuzzy sets, C_q a the consequent class, CF_q is the confidence of the rule R_q, and N is the total number of generated fuzzy if-then rules. The confidence plays a role of weight in the fuzzy inference process. It is shown in [3] that any non-linear function can be realized by modifying the confidence. In this paper, the adaptation process is effectively implemented by the modification of the confidence for fuzzy if-then rules in the constructed fuzzy rule-based classifier according to the newly available training patterns.

We use triangular membership functions as antecedent fuzzy sets. Figure 1 shows triangular membership functions which divide the attribute axis into five fuzzy sets. Suppose that an attribute axis is divided into L fuzzy sets.

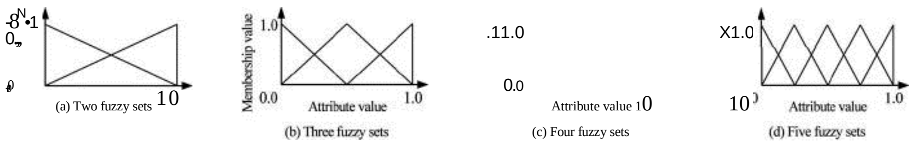

Fig. 1 Triangular fuzzy sets.

4 Incremental Construction of Fuzzy Rule-Based Classifiers

Since not all training patterns are available at a time but are available over time, it is necessary for already generated fuzzy if-then rules to adapt themselves to the training patterns that are newly made available. In this paper three methods for incrementally constructing fuzzy rule-based classifiers are proposed. The three methods update the summed compatibilities that are calculated in (??), but in different manners.

Incremental method A: In the confidence calculation, all available training patterns are equally handled.

Incremental method B: The confidence update is performed according to so-called delta rule.

Incremental method C: The new confidence is calculated so that the weight for the previous training patterns are discounted and the latest training patterns have the largest weight.

Due to the page limitation, the exact calculation for the three incremental methods above are omitted.

5 Computational Experiments

This section examines the performance of the incremental methods that are described in Section 4. Specifically, the adaptability of the incremental methods is evaluated through computational experiments where a two-dimensional dynamic problem is used. Figure 2 shows the dynamic problem that is used in the computational experiments in this paper. There are four classes in the problem and they rotate with the center point at (0.5,0.5). The rotation rate of the classification boundaries is one degree per time step (i.e., after 360 time steps, the classification boundaries coincide with the initial state).

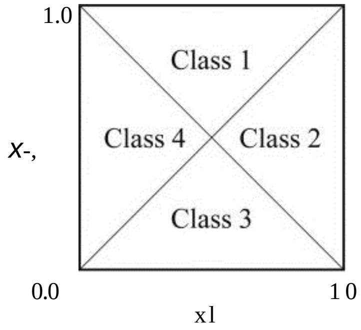

Fig. 2 Initial state of the dynamic pattern classification problem.

During the experiments, the generalization ability is examined by generating test patterns on the grid that splits each axis into 100 segments (i.e., 0.0, 0.01, 0.02, ... , 0.98, 0.99,1.0), making 10201 test patterns with calculated class from the current decision boundaries at each time step. The test patterns are then classified with the updated fuzzy rule-based classifiers. Classification rate for the 10201 patterns is employed as the performance measure.

The experimental results by Method A, Method B, and Method C are shown in Figs. 3, 4, and 5, respectively. From Fig. 3, it is shown that the classification rate goes up only in the beginning of the experiments (from Time 0 to around Time 50). This is because Method A equally considers the weight of all training patterns that have been made available. This is also why the classification rate by Method A recovers at the end of the experiment as the classification boundaries at Time 360 is exactly the same as the ones at Time 0. The classification rates by Method B and Method C are not worse than Method A as these methods discount the weight for previously available training patterns and put more focus on those patterns that are made available more recently. Although the classification rate goes up and down during the experiments, both Method B and Method C are proved to be adaptive enough to the dynamic change in the classification boundaries.

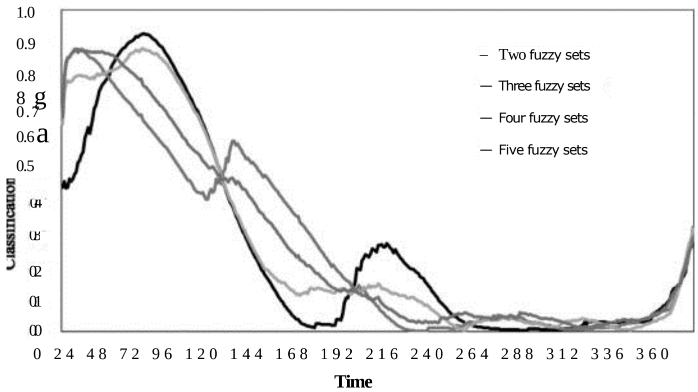

Fig. 3 Classification rate by Method A.

6 Conclusions

Three incremental methods for fuzzy rule-based classifiers were proposed and examined in this paper. The target classification problems are supposed to give streaming training patterns that are made available over time. Fuzzy if-then rules have to be updated according to the new training patterns. The experimental results suggest that previously available training patterns should not be considered equally to the latest available training patterns. The future works include developing the way

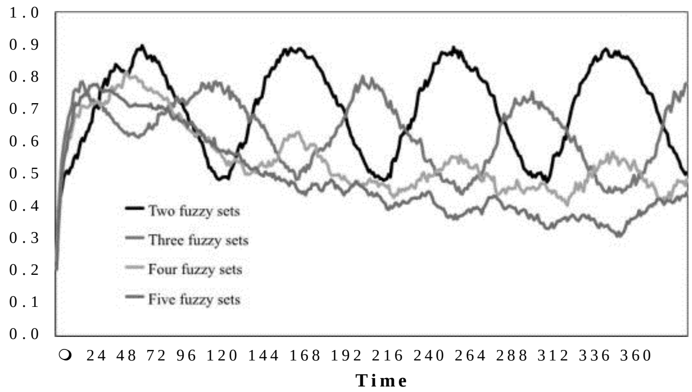

Fig. 4 Classification rate by Method B.

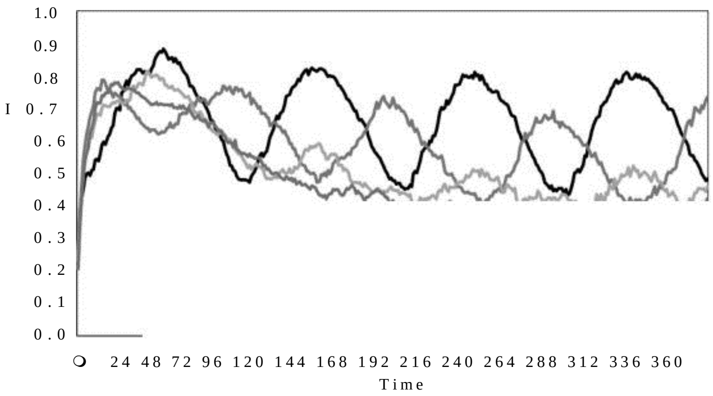

Fig. 5 Classification rate by Method C.

to evaluate the dynamism of the problem. That is, the fuzzy rule-based classifiers should be able to monitor the dynamic change in the classification problem so that the fuzzy rule-based classifiers can adapt themselves accordingly. Designing an appropriate measure of dynamism is also the key step in order for fuzzy rule-based classifiers to moderate the adaptability of the incremental update.

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