Fuzzy Classifications Using Fuzzy Inference Networks

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Abstract—In this paper, fuzzy inference models for pattern classifications have been developed and fuzzy inference networks based on these models are proposed. Most of the existing fuzzy rule-based systems have difficulties in deriving inference rules and membership functions directly from training data. Rules and membership functions are obtained from experts. Some approaches use backpropagation (BP) type learning algorithms to learn the parameters of membership functions from training data. However, BP algorithms take a long time to converge and they require an advanced setting of the number of inference rules. The work to determine the number of inference rules demands lots of experiences from the designer. In this paper, self-organizing learning algorithms are proposed for the fuzzy inference networks. In the proposed learning algorithms, the number of inference rules and the membership functions in the inference rules will be automatically determined during the training procedure. The learning speed is fast. The proposed fuzzy inference network (FIN) classifiers possess both the structure and the learning ability of neural networks, and the fuzzy classification ability of fuzzy algorithms. Simulation results on fuzzy classification of two-dimensional data are presented and compared with those of the fuzzy ARTMAP. The proposed fuzzy inference networks perform better than the fuzzy ARTMAP and need less training samples.

I. INTRODUCTION

Classification of objects is an important area in a variety of fields, including pattern recognition, artificial intelligence, and vision analysis. In a pattern classification problem, if the a priori probabilities and the state conditional densities of all classes are known, Bayes decision theory produce optimal results in the sense that it minimizes the expected error rate. However, in many pattern recognition problems, such information is not available. In this case, many other algorithms such as nearest prototype algorithm, K-nearest neighbor (K-NN) algorithm, and neural network classification algorithms are used.

Conventional nonfuzzy or crisp classification techniques assume that a pattern \( X \) belongs to only one class. Fuzzy classification algorithms assign the pattern \( X \) with a distributed membership value to each class. The partitions between fuzzy classes are “soft.” Since 1965, many efforts have been dedicated to fuzzy classification and many algorithms have been presented and applied in pattern recognition and decision systems. Among all the work that has been done, fuzzy K-nearest neighbor algorithm by Keller et al. [1] and fuzzy c-means algorithm by Bezdek [2] are the most important ones for pattern recognition problems. Pedrycz gave a survey [3] on fuzzy classification methods and their applications.

Fuzzy classifier design can be performed by supervised learning using a set of training data with fuzzy or nonfuzzy labels. When given a pattern, the fuzzy classifier computes the membership value of the pattern in each class and makes decisions based on these membership values. The fuzzy labels of a fuzzy classifier can be “defuzzified” and then the fuzzy classifier becomes a hard classifier but uses the idea of fuzziness in the model. Fuzzy classifier design almost always means arriving at a hard classifier because most pattern recognition systems require hard labels for objects being classified. We can find a better solution to a crisp problem by looking in a larger space at first, which allow the algorithm more freedom to avoid errors. Fuzzy classification algorithms have advantages when a) the decision maker needs the information of classification uncertainty [4], [5]; b) the features of patterns involve uncertainty [5], [6]; and c) it is difficult to find a hard boundary in a classification problem [6], [7].

On the other hand, neural networks (NN’s) have been used as pattern classifiers in many applications in recent years [8]–[14]. Neural network classifiers are model-free estimators [11]–[12]. Neural network classifiers do not make assumptions of how outputs depend on inputs. Instead, they adjust themselves to a given training set by a learning algorithm and decide the boundaries of classes [13], [14].

It is of practical interest to combine fuzzy classification techniques and neural networks while preserving advantages of both and avoiding their problems. Some researchers have combined these two techniques. We have proposed a fuzzy neural network (FNN) for character pattern recognition [15], [16]. This FNN can recognize shifted and distorted training patterns. Keller and Hunt [18] introduced fuzzy set theory into perceptron algorithm. Their fuzzy perceptron converges quickly when the classes are overlapping. This algorithm assigns the fuzzy membership functions before training the perceptron classifiers. Archer and Wang [19] developed a monotonic function neural network model and used it to represent fuzzy membership functions in two-class pattern recognition problems. This model used several small NN’s to construct the boundary of classes. Its applications are limited because it can only deal with two-class monotonic classifications. Kuo et al. proposed a fuzzy neural network.
IF (there is one \( c_p > E_t \quad (p = 1 \text{ to } P) \)) \( \sigma > E_t \), THEN
adjust \( t_{ij}^1 \) and \( t_{ij}^2 \quad (i = 1 \text{ to } N, j = 1 \text{ to } m) \) until \( c_p \leq E_t \quad (p = 1 \text{ to } P) \).

IF (there is one \( c_p < -E_t \quad (p = 1 \text{ to } P) \)), THEN
add a new MIN-FN in layer 2 and increment \( m \),
adjust the weight functions \( w_{im}^1 (i = 1 \text{ to } N) \) and weights \( w_{mp}^2 (p = 1 \text{ to } P) \).
increment \( k \)
END DO UNTIL
END DO UNTIL
END

Self-organizing learning algorithm for the MSFIN classifier:

BEGIN
set \( E_t \), establish layer 1 and layer 3,
establish the 1st MIN-FN in layer 2 for the 1st training sample,
adjust the weight functions \( w_{ij}^1 \) and weights \( w_{ip}^2 \),
initialize \( m = 1, k = 2 \).
DO UNTIL \( (k \geq K) \)
input the \( k \)th training pattern, compute the output errors:
\( c_p = s_{kp}^2 - d_{kp} \), \( (p = 1 \text{ to } P) \)
IF (there is one \( |c_p| > E_t \quad (p = 1 \text{ to } P) \)), THEN
add a new MIN-FN in layer 2 and increment \( m \),
adjust weight function \( w_{ij}^1 (i = 1 \text{ to } N, j = 1 \text{ to } m) \) and \( w_{jp}^2 (j = 1 \text{ to } m, \quad p = 1 \text{ to } P) \).
increment \( k \)
END DO UNTIL
let \( \sigma = \max_k \left( \max_p |c_p| \right) \)
DO UNTIL \( (\sigma < E_t) \)
initialize \( k = 1 \)
DO UNTIL \( (k \geq K) \)
input the \( k \)th training samples and compute the output error
IF (there is one \( |c_p| > E_t \quad (p = 1 \text{ to } P) \)), THEN
add a new MIN-FN in layer 2 and increment \( m \),
adjust weight function \( w_{ij}^1 (i = 1 \text{ to } N, j = 1 \text{ to } m) \) and \( w_{jp}^2 (j = 1 \text{ to } m, \quad p = 1 \text{ to } P) \).
increment \( k \)
END DO UNTIL
END DO UNTIL
END

REFERENCES
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