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퍼지 신경 회로망을 이용한 패턴 분류기의 설계

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Design of the Pattern Classifier using Fuzzy Neural Network

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Abstract - In this paper, we discuss a fuzzy neural network classifier with immune algorithm. The fuzzy neural network classifier is constructed with the fuzzy classifier and the neural network classifier based on fuzzy rules. To maximize performance of classifier, the immune algorithm and the back propagation algorithm are used. For the generalized classification ability, the simulation results from the iris data demonstrate superiority of the proposed classifier in comparison with other classifier.

Index Term - Fuzzy classification, neural network, immune algorithm, back propagation algorithm.

1. Introduction

Over the last few years, there has been an ever-increasing interest in the area of classification system [1]. Numerous attempts have been made by researchers to solve the classification problems. Fuzzy theory also applied to classification system successfully. The fuzzy classifier is interpretable and analyzable due to representing the linguistic form and the discriminant function, and also has the excellent capability to classification [2-4]. In spite of the advantage, the fuzzy classifier has the following limitation: Fuzzy methods are cumbersome to use in high dimensions or on complex problem, and the amount of information that can be expected to bring to a problem by designer is quite limited. In addition, much ink has also been spent on neural network classification systems. The neural network classifier has a little certain disadvantage: they are computationally expensive, and require a few parameters that can only be determined through experiment [1]. Despite of these disadvantages, the neural network has following two important advantages that make them comparable to the statistical classifier and the fuzzy classifier: neural network classifiers are distribution free, and are importance free. [7]

On the other hand, classification problems that contain highly complex data such as the sensory data from multiple sensors and the signal data have increased currently. The complexity of classification data makes a level of classification problem hard. To solve these classification problems, new advanced classifier based on a conventional classifier, combined classifier is required.

In this paper, we present new combined classifier that combines fuzzy classifier and neural network classifier to overcome limitation of conventional classifier. The structure of Combined fuzzy neural network classifier (FNNC) is based on multi inputs and multi outputs (MIMO) fuzzy model. Each rule acts like a "local classifier" by using the fuzzy classifier. The consequents of each rule are represented local neural network classifier. The Local neural network classifier has a simple structure based on multi-layer neural network, and uses back-propagation algorithm for classifier tuning. Finally, the fuzzy classifier of FNNC is tuned using the immune algorithm that implements the immune system of human body.

2. A New Approach to Fuzzy Neural Network Classifier.

We present a new type of fuzzy neural network classifier that inspired by both the neural network classifier and the fuzzy classifier. A typical fuzzy neural classifier can be described by a set of following fuzzy rules:

$$R_i:\ IF\ x_1\ is\ A_{i1}\ \text{and}\ x_2\ is\ A_{i2}\ \ldots\ \text{and}\ x_M\ is\ A_{iM}\quad THEN\ y_i=[y_i^1\ \ldots\ y_i^N] \tag{1}$$

where R_i is the i th rule $(1\le i\le N)$; $x_j(1\le j\le M)$ is the jth feature of x; M is the number of feature; N is the number of class; y_i^j is the output of the jth output node of the ith neural network.

$$y_i^k=f(\sum_{j=1}^{n_H} w'^i_{kj}\, f(\sum_{g=1}^{d} w^i_{jg}x_g)) \tag{2}$$

The output of classifier $\hat{Y}$ is then determined by the rule that has the highest degree of activation:

$$\hat{Y} = \hat{y}_{i^*}, \quad i^* = \arg\max y_i, \quad (1 \le i \le N) \tag{3}$$

The output of each rules $\hat{y}_i$ is defined as

$$\hat{y}_i = \frac{\sum_{k=1}^{N} w_k y_i^k}{\sum_{j=1}^{N} w_j} \tag{4}$$

where $w_k = \prod_{j=1}^{M} \mu A_{ij}(x_j)$ $\mu A_{ij}(x_j)$ is the degree of membership function.

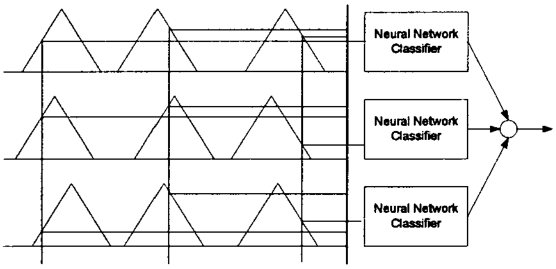

Fig. 1. Structure of FNNC

Figure 1 shows the structure of fuzzy neural network classifier. Each fuzzy rule has its neurual network classifier.

3. Optimization of FNNC

3.1 Optimization Concept

Since the proposed classifier is constructed with two kinds of different classifiers, we need to tune the proposed classifier separately. The premise part of classifier uses the immune algorithm for the classifier tuning and the conclusion part of classifier uses back-propagation algorithm for the classifier tuning.

Remark 1 *To guarantee that $\widehat{y_i}$ is larger than $\widehat{y_j}$, the immune algorithm and the back-propagation algorithm must satisfy the following condition*

$$w_i > w_j \quad and \quad y_k^i > y_k^j \, . \tag{5}$$

3.2 Tuning neural network classifier using back propagation algorithm

The Back propagation algorithm are one of the simplest and most general methods for supervised training of multi-layer neural networks [5]. We consider training error on a pattern to be the sum over output units of the squared difference between the desired output given by the supervisor and the actual output. To satisfy (5), the back-propagation algorithm has the following training data.

$$d_i = [\, t_1\, t_2\, t_3 \, . \, . \, t_i \, . \, . \, t_M] t_i = 1, \; t_{j \neq i} = 0 \tag{6}$$

where d_i is the training data for the ith neural network classifier.

Back-propagation algorithms are based on gradient descent methods. The weights of node are initialized with random values, and then they change in the direction such that reduces the error.

$$\Delta w_{qp} = -\eta \frac{\partial J}{\partial w_{qp}} \tag{6}$$

where η is the learning rate, and Δw_{qp} indicates the relative size of the change of weight w_{qp}. The change of hidden-to-output weights, w_{kj} can be calculated using the chain rule for differentiation. Assume that activation function $f(\cdot)$ is differentiable, we have

$$\Delta w_{kj} = \eta \delta_k y_j = \eta (d_k - z_k) f'(net_k) y_j. \tag{7}$$

$$\delta_k = -\partial J / \partial net_k = (d_k - z_k) f'(net_k) \tag{8}$$

where δ_k is sensitivity of unit k.

Along with a similar line, the change of input-to-hidden weights, w_{jg} is

$$\Delta w_{jg} = \eta x_i \delta_g = \eta \left[\sum_{k=1}^{c} w_{kj} \delta_k \right] f'(net_k)\, x_i \tag{9}$$

$$\delta_k \equiv f'(net_j) \sum_{k=1}^{c} w_{kj} \delta_k \tag{10}$$

3.3 Tuning fuzzy classifier using immnune algorithm

An Immune algorithm is derived from an immune system. The immune system can detect and eliminate the non-self materials such as virus and cancer cells that originate from inside or outside of the human system. Therefore, the immune system has the antigen and the antibody that describe non-self and self of materials [6]. Note that there are various sets of antibodies that can be produced in immune system. However, an antibody can specifically recognize only an antigen.

The main immune aspects to be taken into account to develop the algorithm are: 1) maintenance of a specific memory set; 2) selection and cloning of antibodies; 3) death of non-selected antibodies; 4) The affinity maturation; and 5) The reselection of the clone proportionally to their affinities. Figure 2 shows the computational procedure of immune algorithm. The Procedure of Immune algorithm can be described as the following:

1) Randomly choose an antigen A_{g_k} and presents it to all Antibody in the repertoire. To optimize the parameter of fuzzy classifier, the main antibody Ab_{ij} is constructed sub-antibodies that represent fuzzy membership function.. The notation i is the number of class and j is the number of feature.

2) Determine the vector f_j that contain affinity of Ag_j to all N Antibody in Ab. The Affinity is evaluated using object function $f_{obj}(x)$ that return

fuzzy degrees that calculated from fuzzy set. The object function can be described as the following equation.

$$f_{obj}(x) = e^{\left(\frac{(x-m)^2}{2v^2}\right)}, \quad class_{ag} = class_{ab}$$
$$= -e^{\left(\frac{(x-m)^2}{2v^2}\right)}, \quad class_{ag} \neq class_{ab} \tag{10}$$

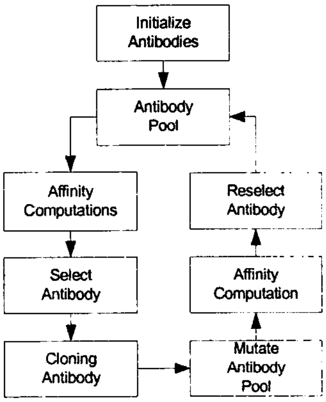

Fig. 2. Computational Procedure of Immune algorithm

3) Select the n highest affinity antibody from Ab_{ij} to compose a new set of $Ab^{k}_{ij(n)}$ of high-affinity antibody related to A_{g_r}.

4) The n selected antibody will be cloned independently and proportionally to their affinities, and then generate a repertoire C_k of clones.

5) The repertoire C_k is submitted to an affinity maturation process, generating a population C_k^* of matured clones.

6) In mutation process, antibodies are mutated until affinities of them are greater than f_j or loop counter is over maximum loop.

7) Determine affinity f_j^* of matured clones C^k in relation to antigen Ag_j.

8) From those sets of clones C_k^*, reselect the one with highest affinity A_j^* in relation to Ag_j to be a candidate to enter the set of memory antibodies $Ab_{\{m\}}$.

9) Finally, replace the m lowest f_j^* antibodies from Ab with the m highest f_j candidate antibodies from C_k^*.

4. Computer simulations

The Fisher iris data consist of 150 data with four input features and three classes. In this paper, the training data and the testing data is composed 150 data in the iris data. Table 1 shows the performance of various classifier and proposed classifier. In terms of the rule number and the recognition rate, the proposed fuzzy neural network classifier is superior to the other fuzzy-rule-based classifier.

Table 1 Classification Performances

Ref.	Number of rules	Recognition rate
[2]	5	96.67%
[3]	8	96.3%
[4]	4	97.33%
Ours	3	98.67%

5. Conclusions

In this paper, we proposed the fuzzy neural network classifier. Significantly, our classifier combined the fuzzy classifier and the neural network classifier to solve classification problems that include complex data. In addition, the immune algorithm was used for optimization of our classifier. Simulation results on iris data demonstrated that the classification accuracy and the fuzzy rule number of the proposed classifier were comparable to the other fuzzy classifier.

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