Research on the Method of Neural Network Modeling Based on FCM Algorithm and Its Application on Vision-based Sensors

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Abstract

This paper proposes a novel fuzzy neural network model based on fuzzy clustering method. The model can accept continuous and discrete inputs together; the discrete input to the model is divided into several clusters by using fuzzy c-mean clustering algorithm (FCM). A fuzzy clustering neuron (FC-neuron) is designed to calculate a membership degree value belonging to one cluster for each discrete input. A four-layer hybrid neural network is constructed; fuzzy-neurons and FC-neurons construct the antecedent part of fuzzy rules. A multi-input multi-output hybrid neural network was designed by the novel modeling method and applied to vision-based sensors. Simulation results show this method is superior to the traditional neural network model in vision-based sensors.

1. Introduction

Traditional neural network models usually only accept continuous inputs and the discrete inputs, for example, scenario A, B, C, etc., should be transferred or quantified to continuous value. But in some applications, the discrete inputs cannot be quantified because scenarios are complicated and important. How to use these discrete inputs to neural network modeling has no good way yet. Some researchers proposed FCM algorithm to cluster discrete inputs, then classify these inputs to some groups and weight them as inputs of neural network[1][2]. In this paper, a novel fuzzy neural network model based on fuzzy clustering method was proposed. Vision-based sensor used in intelligent vehicles system to recognize road status is taken as the application of new modeling way. Because many road statuses are hard to quantify and haven’t been taken as the patterns or features before, by the proposed method we try to transfer these statuses as neural network’discrete inputs and give a more accurate results to recognition.

2. Fuzzy C-mean Clustering Algorithm

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method (developed by Dunn in 1973[3] and improved by Bezdek in 1981[4]) is frequently used in pattern recognition. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} ||x_i - c_j||^2$$  \hspace{1cm} (1)

where m is any real number greater than 1, $u_{ij}$ is the degree of membership of $x_i$ in the cluster $j$, $x_i$ is the ith of d-dimensional measured data, $c_j$ is the d-dimension center of the cluster, and $||\cdot||$ is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership $u_{ij}$ and the cluster centers $c_j$ by:

$$u_{ij} = \frac{1}{C \sum_{k=1}^{C} \left( \frac{||x_i - c_j||^2}{||x_i - c_k||^2} \right)^{m-1}}$$ \hspace{1cm} \sum_{i=1}^{N} u_{ij}^{m} x_i$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$  \hspace{1cm} (2)

This iteration will stop when $\max_{ij} \left\{ |u_{ij}^{(k+1)} - u_{ij}^{(k)}| \right\} < \varepsilon$, where $\varepsilon$ is a termination criterion between 0 and 1, whereas $k$ are the iteration steps. This procedure converges to a local minimum or a saddle point of $J_m$.

The algorithm is composed of the following steps:
a. Initialize $U = [u_{ij}]$ matrix, $U^{(0)}$;

b. At k-step: calculate the centers vectors $C^{(k)} = [c_j]$ with $U^{(k)}$;

$$c_j = \frac{\sum_{i=1}^{N} u_{mj}^m x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

(3)

c. Update $U^{(k)}$, $U^{(k+1)}$,

$$u_{ij} = \frac{1}{2} \frac{C}{\sum_{k=1}^{C} \left( \frac{||x_i - c_j||^2}{||x_i - c_k||^2} \right)^{m-1}}$$

(4)

d. If $||U^{(k+1)} - U^{(k)}|| < \varepsilon$ then STOP; otherwise return to step 2.

Using FCM algorithm, the samples will be clustered into some classes. The degrees of membership of samples are calculated by (4).

3. Hybrid Fuzzy Neural Network Using FCM

In this paper, a four-layer fuzzy neural network proposed in [5] was adopted as the prototype of new hybrid fuzzy neural network. As shown in Fig.1,

![Figure 1: a four-layers structure of FNN](image)

the fuzzy neural network is an n-input, 1-output, and m-rule fuzzy neural network, which has four layers: input layer, fuzzification layer, fuzzy reasoning layer and output layer. Each node of the fuzzification layer performs a Gaussian membership function. The fuzzy reasoning layer performs IF-condition reasoning by a product operation. Each linguistic variable has just one linguistic value allowed to connect one rule node. The output layer computes the overall output as the summation of all incoming rule activation intension and performs the defuzzification. The node function of each layer was expressed by:

$$y_i^1 = x_i^1; \quad y_j^2 = \exp[-(x_i^2 - m_{ij})^2/\sigma_{ij}^2]; \quad y_k^3 = \prod_i x_i^3; \quad y_o^4 = \sum_k w_k^4 x_k^4$$

(5)

Train the FNN to adjust $m_{ij}$ and $\sigma_{ij}$ by Kohonen’s self-organizing feature maps and make the FNN fit the test pairs obtained. Choose fuzzy rules by competitive learning algorithm, and eliminate redundant rules that have less weight between rule nodes and output node. Adjust membership function and weights by back-propagation algorithm until meet the error function:

$$E = \frac{[y(t) - \hat{y}(t)]^2}{2}$$

(6)

where $y(t)$ is the desired output, and $\hat{y}(t)$ is the current output.
For constructing new modeling way to accept continuous and discrete inputs together, we proposed a new structure of neural network modeling. It was named Continuous-Discrete Hybrid Inputs Fuzzy Neural Network (for short, HybridINP-FNN). The structure of HybridINP-FNN is like the four-layer FNN, also named input layer, fuzzification layer, fuzzy reasoning layer and output layer, shown in Fig.2:

1) Input layer: input layer nodes transfer the input directly to next layer, some nodes receive continuous inputs, other nodes receive discrete inputs:

\[ net^1_i = x^1_i, \quad y^1_i = f^1_i(net^1_i) = x^1_i, \quad i \in [1,m] \tag{7} \]

\( x^1_i, y^1_i, net^1_i \) and \( f^1_i \) denotes the input, output, net input and activation function of \( i \)th node of input layer respectively (the symbols of other layer by parity of reasoning).

2) Fuzzification layer: there are two kinds of nodes, one kind is Gaussian membership function node to calculate a membership for continuous inputs:

\[ net^2_i = -\frac{(x^1_i - m^1_j)^2}{2\sigma^2_j}, \quad y^2_j = f^2_j(net^2_j) = \exp(net^2_j), \quad i \in [1,n] \tag{8} \]

Another kind is fuzzy clustering node to calculate the membership for discrete inputs based on a membership matrix which is the result of fuzzy clustering to discrete inputs. These nodes are named as FC-neurons. The parameter of fuzzy clustering nodes are fixed so that there is no need to change in neural network training. We got the membership matrix of \( i \)th discrete input based on FCM algorithm:

\[ U_i = (u_{IJ})_{c_i \times N_i} \tag{9} \]

where \( c_i \) is the cluster number of discrete input \( x_i \) (\( I = 1, 2, \ldots, c_1 \)), also is the fuzzy clustering nodes number; \( N_i \) is the number of discrete elements of discrete input \( x_i \) (\( J = 1, 2, \ldots, N_i \)); the matrix element \( (u_{IJ})_i \) denote the degree of \( i \)th input belong to \( I \)th cluster \( (\omega_I)_i \); the membership function of the \( j \)th FC-neurons is:

\[ net^3_j = x_i, \quad y^3_j = f^3_j(net^3_j) = (u_{IJ})_i, \quad i \in [n+1,m] \tag{10} \]

By this way, the output of second layer are all fuzzification value to the input of the first layer.

3) Fuzzy reasoning layer: The fuzzy reasoning layer performs IF-condition reasoning by a product operation. Each linguistic variable has just one linguistic value allowed to connect one rule node.

4) Output layer: The output layer computes the overall output as the summation of all incoming rule activation intension and performs the defuzzification.
4. Application

In our vision-based sensor project, a negative model was constructed by proposed hybrid FNN for accepting discrete inputs - environments changes except continuous digital vision signals. An experiment was designed to compare the new hybrid FNN method to four layer FNN method. There are 1200 input-output parameters sampled or computed in each sampling period (100ms). A database composed of 89554 observation pairs is gained in the end. Some data are set as training pairs, and other data as test pairs. For designing hybrid FNN, we began to compute using the training pairs. 56 fuzzy rules was predefined respectively to continuous and discrete inputs, the parameters of the initial hybrid FNN were selected by the on-line initialization method proposed. After the first network training, a few fuzzy rules were eliminated respectively because of their low weight. So 34 fuzzy rules was kept down in the end. After secondly adjusting network parameters, the assessment of the generalization performance of the hybrid FNN was done by the test pairs. The experimental results are desirable. The average prediction error is less than 4%. For assessing the advantage of the hybrid FNN, the four-layer FNN are used to compare with hybrid FNN on training. The result is that the hybrid FNN obtains higher accuracy with less training time than four-layer FNN methods in vision-based sensor application.

5. Conclusion

This paper presented a novel neural network modeling method based on fuzzy clustering algorithm to train continuous and discrete inputs. Firstly, FCM algorithm was adopted to cluster input samples into classes, then corresponding cluster neuron was design to give fuzzy values to different discrete inputs. Based on the fuzzy cluster neuron and Gaussian neuron, a hybrid FNN structure was proposed. To vision-based sensor, we designed a new way for statues alternation based on new modeling method. A few key patterns are therefore selected as the inputs of hybrid FNN. The advantage of the hybrid FNN and its train methods is that it has more accuracy than contrastive RBFN and FNN algorithm.

REFERENCES