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A New Fuzzy Neural System with Applications

Yuanyuan Chai [1], Jun Chen [1] and Wei Luo [1]

1 -China Defense Science and Technology Information Center -Network Center
Fucheng Road 26#, Haidian district, Beijing -China

Abstract. Through a comprehensive study of existing fuzzy neural systems, this paper presents a Choquet integral-OWA operator based fuzzy neural system named AggFNS as a new hybrid method of CI, which has advantages in universal fuzzy inference operators and importance factor expression during reasoning process. AggFNS was applied in traffic level of service evaluation problem and the experimental results showed that AggFNS has great nonlinear mapping function and approximation capability by training, which could be used for complex systems modeling, prediction and control.

1 Introduction

Since its birth in 1992 [1], computational intelligence (CI) has emerged as a new field of study and gained widespread concern from a growing number of scholars, the main branches of which are fuzzy logic (FL), neural network (NN), evolutionary computing (EC). In large measure, fuzzy logic, neural computing, and probabilistic reasoning are complementary, not competitive [2]. Research on hybrid algorithms has been the hot issues in CI study and obtained good results in practical applications.

Through an in-depth understanding of fuzzy neural system and a comparative analysis of existing models, this paper will introduce a new hybrid method: Choquet integral-OWA operator based fuzzy neural system. Its model validity will be tested by traffic sample data.

2 Existing fuzzy neural systems

Neural network structures can deal with imprecise data and ill-defined activities. However, the subjective phenomena such as reasoning and perceptions are often regarded beyond the domain of conventional neural network theory. It is interesting to note that fuzzy logic is another powerful tool for modeling uncertainties associated with human cognition, thinking and perception [3][4]. In fact, the neural network approach fuses well with fuzzy logic and some research endeavors have given birth to the field of “fuzzy neural networks” or “fuzzy neural systems” [5][6].

There are a lot of theories and ideas for combining fuzzy logic and neural networks. Takagi and Hayashi were pioneers in the study on fusion of these two algorithms [7]. C.T. Lin, C.S.G. Lee [8] and L.X. Wang, J.M. Mendel [9] have also proposed structures of fuzzy neural systems respectively.

J. S. Jang proposed ANFIS that represented the Takagi–Sugeno–Kang model which can be used for controller design and evaluation [10]. T-S fuzzy inference system works well with linear techniques and guarantees continuity of the output surface. But the consequent linear expression of ANFIS couldn’t sufficiently reflect

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the human thinking process and ANFIS has difficulties in assigning importance (weight) to each input and fuzzy rule.

Mamdani model based fuzzy neural system can show its legibility and understandability to the laypeople and has advantages in consequent expression and intuitive reasoning, which does well in solving multi-criteria evaluation problems. But it needs large calculation amount for defuzzification and also has difficulties in importance (weight) expression.

So there are the following two major disadvantages in the existing models:

- Importance (weight) of each input and each rule is not considered, which means their contribution to the overall output is same during the reasoning. This is not consistent with human cognition.
- The choice of inference operators is relatively fixed and reasoning composite method is also limited to max-min and sum-product. The essence of fuzzy neural systems is non-linear mapping and each step of fuzzy reasoning is also a non-linear mapping process, which means other reasoning operators could be used to achieve the reasoning step in addition to traditional inference operators.

3 Choquet integral-OWA operator based fuzzy inference system

In order to solve these shortcomings and model a new fuzzy neural system, this paper first presents a Choquet integral-OWA operator based fuzzy inference system named AggFIS.

In the inference layer, OWA operator is applied to replace AND (OR) operator and calculate firing strength [11]; in the aggregation layer, Choquet integral instead of the traditional T-conorm operator is used to aggregate the qualified MFs and generate an overall output MF; and the defuzzification operator is centroid of area (COA). Furthermore, in the reasoning process the importance (weight) of each input is expressed by μ_i and weight of each rule is expressed by τ_i. All these FIS steps are regarded as aggregation process and the replaced operators can be expressed as "Agg". The reasoning process of AggFIS is shown in Figure 1.

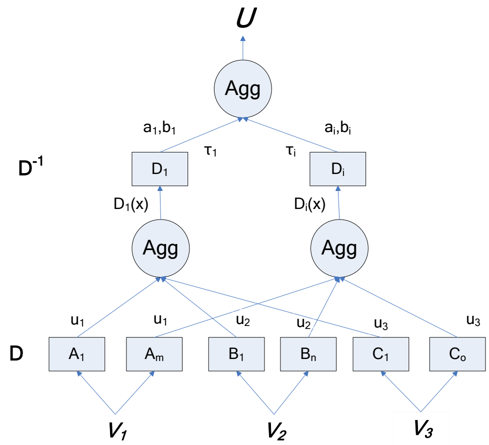

Fig. 1: Choquet integral-OWA operator based fuzzy inference system.

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The format of fuzzy rule is as follows:
If V_1 is A_m and V_2 is B_n and V_3 is C_o, Then U is D_i
($m=1,2,\ldots,p_1$; $n=1,2,\ldots,p_2$; $o=1,2,\ldots,p_3$; $i=1,2,\ldots,n$)

V_1, V_2, V_3 are the crisp inputs, U is the single crisp output; A_m, B_n, C_o represents the membership function of each input variable; D_i represents the membership function of output variable; p_1, p_2 and p_3 are the numbers of input membership functions, and n is the numbers of output membership functions. Where,

- D: membership function for the antecedents (membership neural module);
- D^{-1}: membership function for the consequents (inverse membership neural module);
- $D_i(x)$: firing strength of each rule;
- μ_i: importance (weight) of each input;
- τ_i: importance (weight) of each rule;
- $[a_i, b_i]$: range value for each rule's output.

4 Choquet integral-OWA operator based fuzzy neural system

If Choquet integral-OWA operator based fuzzy inference system (AggFIS) is incorporated into a feedforward neural network, we obtain the adaptive model for AggFIS, which is Choquet integral-OWA operator based fuzzy neural system named AggFNS. It has the ability of learning and the adaptability to the data.

4.1 Model description

We assume AggFNS under consideration has two inputs x and y and one output f. The rule base contains two fuzzy if-then rules:
Rule 1: If x is A_1 and y is B_1, Then f is C_1;
Rule 2: If x is A_2 and y is B_2, Then f is C_2.

AggFNS model consists of five layers which are shown in Figure 2. Output of each layer is as following, where $O_{i,j}$ means the jth output in the ith layer.

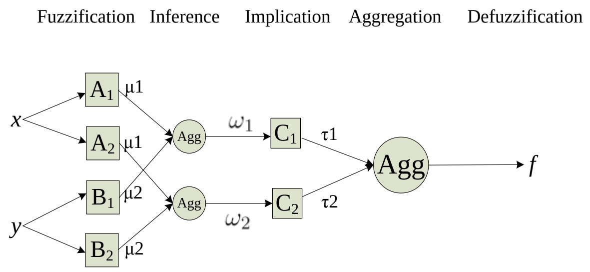

Fig. 2: AggFNS model.

Layer 1: fuzzification layer:

Generate the membership grades $\mu_A(x)$, $\mu_B(y)$.

$$O_{1,i} = \mu_{A_i}(x) \qquad i=1,2 \quad (1)$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad i=3,4 \quad (2)$$

The membership function is the generalized bell function:

$$\mu_{Ai}(x) = \frac{1}{1+[(\frac{(x-c_i)}{a_i})^2]^{b_i}} \qquad (3)$$

Where A_i, B_i are input MFs, $\{a_i, b_i, c_i\}$ is the parameter set which refers to premise parameters.

Layer 2: inference layer or rule layer:

$$O_{2,i} = \omega_i = [\bar{\mu}_1 + \mu_1 \times \mu_{Ai}(x)] \times [\bar{\mu}_2 + \mu_2 \times \mu_{Bi}(y)] \qquad \text{i=1,2} \quad (4)$$

Generate firing strength ω_i by OWA operator, where μ_i indicates the importance (weight) of each input.

Layer 3: implication layer:

$$O_{3,i} = \omega_i \circ C_i \qquad \text{i=1,2} \quad (5)$$

Implication operator is product. C_i is output MFs and the consequent parameters are determined by C_i.

Layer 4: aggregation layer:

$$O_4 = \sum (\omega_i \circ C_i - \omega_{i-1} \circ C_{i-1}) \times \tau_i \qquad \text{i=1,2} \quad (6)$$

Aggregation operator is Choquet integral, where τ_i indicates the importance (weight) of each rule.

Layer 5: defuzzification layer:

$$O_5 = f = D \circ O_4 \qquad (7)$$

Compute the crisp output f. The defuzzification method (D) is COA (center of area).

4.2 Learning rules for AggFNS

In AggFNS model, we use back propagation as the basic learning rule which means gradient vector in steepest descent method is used to update all the nonlinear parameters [12]. Once the gradient is computed, regression techniques are used to update parameters in the model and the parameters updating formula for AggFNS is:

$$\omega_{next} = \omega_{now} + \triangle\omega_{ij} \qquad (8)$$

$$\triangle\omega_{ij} = -\eta \cdot \frac{\partial E}{\partial \omega_{ij}} = -\eta \cdot \frac{\partial E}{\partial x_i} \cdot \frac{\partial f_i}{\partial \omega_{ij}} = -\eta \cdot \varepsilon_i \cdot \frac{\partial f_i}{\partial \omega_{ij}}$$
$$= -\eta \cdot (d_i - x_i) \cdot x_j \cdot X \qquad (9)$$

Where j<i, that is $x_i = f_i(\sum \omega_{ij} \cdot x_j + \theta)$, f_i and ε_i means the activation function and error signal. η is the learning step, d_i is the desired output for node i, x_i is the real output for node i, x_j is the input for node i, X is a Polynomial, which is $X = x_i \times (1 - x_i)$.

5 Experiments

In urban traffic systems, level of service (LOS) is a qualitative measure describing operational conditions within a traffic stream, generally in terms of such service measures as speed and travel time, freedom to maneuver, traffic interruptions, comfort and convenience. Essentially, level of service reflects subjective judgments of drivers about the traffic condition and AggFNS is suitable for modeling the potential mapping relation between LOS inputs and output.

In order to verify the validity of Choquet integral-OWA operator based fuzzy neural system (AggFNS) presented in this paper, we established AggFNS model for LOS evaluation as shown in Figure 3, which are trained and tested by historical sample data (1290 pairs for training and 640 pairs for testing). All nonlinear parameters are adjusted according to formula (8) and (9).

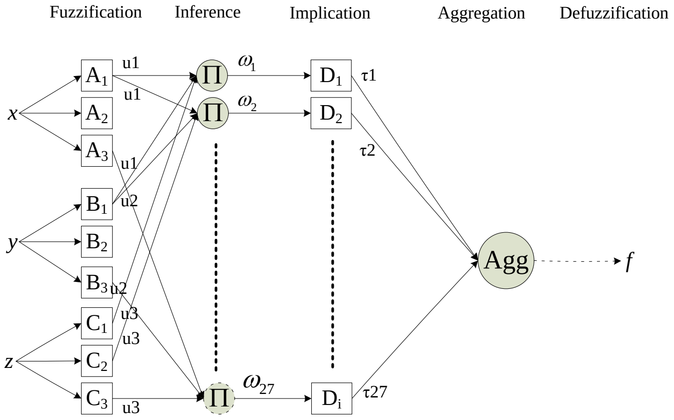

Fig. 3: AggFNS-based evaluation model.

In this model, x, y, z represents the inputs, which are speed, volume, and occupancy. A_1-A_3 represents membership functions of speed; B_1-B_3 represents membership functions of volume; C_1-C_3 represents membership functions of occupancy. D_1-D_6 represents membership functions of LOS output. Rule's format is:

If x is A_r and y is B_s and z is C_t, then LOS=D_i

(r, s, t=1,2,3; i=1,2,…,6)

The training process takes 2.624 second and 750 steps. Mean square error is 0.00022442. Average test error is 0.057391. The worst test error is 0.4154 while the best test error is 1.6785e-005. The desired output (blue) and real output (green) of AggFNS are in Figure 4.

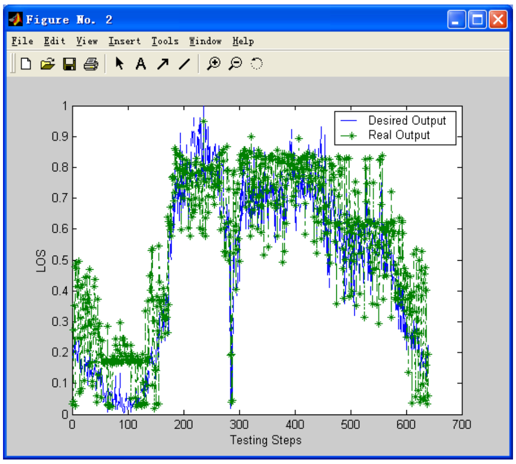

Fig. 4: Desired output and real output of trained AggFNS.

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Table 1 shows the comparison experiment results between ANFIS and AggFNS, which can also verify the superiority of AggFNS.

Model / Results	ANFIS	AggFNS
Parameter Numbers	135	81
Training Steps	1290	750
Training Error	1.0038e-005	0.00022442
Testing Error	0.091368	0.057391
Consuming Time	8.3110	2.624

Table 1: ANFIS and AggFNS experiment results.

The results indicated that AggFNS adapts to sample data well, reflects the essence of traffic LOS precisely and could achieve the desired target due to its infinite approximation capability. Our work could provide a reference for hybrid algorithms study in CI.

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