2 Union-based Fuzzy Neural Networks [5]

This paper is a new application version of the union-based fuzzy neural networks, proposed by the author in [5], to intelligent diagnosis of hepatitis disease. Therefore, the same version of union-based fuzzy neural networks and its optimization method in [5] are used in this paper. For this reason, all of this section directly refers to [5]. For more details about the union-based fuzzy neural networks, please refer to [5].

AND neuron is a nonlinear logic processing element with n-inputs **x** $[0,1]^n$ producing an output y governed by the expression

$$y = \text{AND}(\mathbf{x};\, \mathbf{w}) = \mathop{\mathrm{T}}_{i=1}^{n} (w_i \,\mathrm{s}\, x_i)\,. \tag{1}$$

where **w** denotes an n-dimensional vector of adjustable connections (weights). "s" denoting some s-norm and "t" standing for a t-norm. Individual inputs (coordinates of **x**) are combined *or*-wise with the corresponding weights and these results produced at the level of the individual aggregation are aggregated *and*-wise with the aid of the t-norm.

By reverting the order of the t- and s-norms in the aggregation of the inputs, we end up with a category of OR neurons,

$$y = \text{OR}(\mathbf{x};\, \mathbf{w}) = \mathop{\mathrm{S}}_{i=1}^{n} (w_i \,\mathrm{t}\, x_i)\,. \tag{2}$$

To construct the networks, we first elaborate on the union-based logic processor (ULP) which consists of OR and AND fuzzy neurons, as shown in Fig. 1, where, $\mu_N(x_i)$, $\mu_Z(x_i)$ and $\mu_P(x_i)$ are the membership grades of the fuzzy sets N (negative), Z (zero) and P (positive) for the input variable x_i, i=1,2,3,4, respectively.

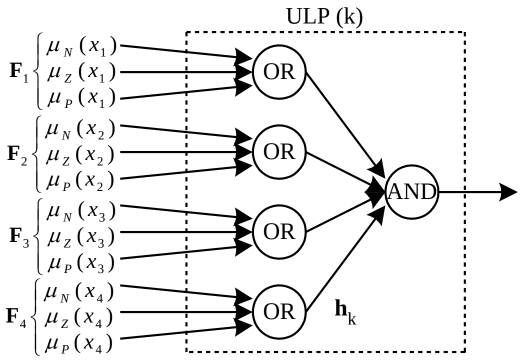

Fig. 1. Structure of an ULP

An important characteristic of ULP is that union operation of input fuzzy sets is allowed to appear in their antecedents, i.e., incomplete structure. For fuzzy system of complex processes with high input dimension, the ULP is preferable because it achieves bigger coverage of input domain compared to the complete structure. For example, consider a system with x_1, x_2 as its inputs and y as its output characterized by three linguistic terms, N, Z and P, respectively. The incomplete structure rule 'If x_1=N then y=N' covers the following three complete structure rules:

(i) If (x_1=N) and (x_2=N) then y=N
(ii) 'If (x_1=N) and (x_2=Z) then y=N
(iii) 'If (x_1=N) and (x_2=P) then y=N

Similarly, the rule 'If (x_1=N or Z) and (x_2=N or Z) then y=N' covers the following four complete structure rules:

(i) If (x_1=N) and (x_2=N) then y=N
(ii) If (x_1=N) and (x_2=Z) then y=N
(iii) If (x_1=Z) and (x_2=N) then y=N
(iv) If (x_1=Z) and (x_2=Z) then y=N

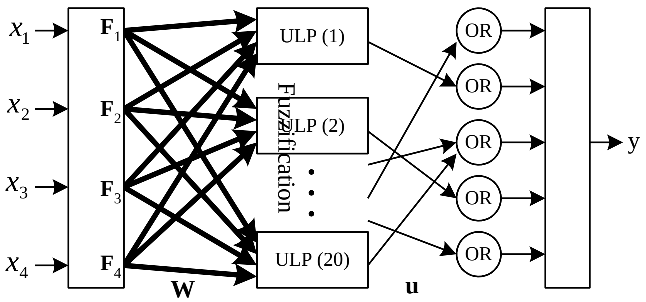

Fig. 2. Structure of union-based fuzzy neural networks with 4 input and 1 output variables characterized by 3 fuzzy sets (NU=20)

Fig. 2 describes the union-based fuzzy neural networks constructed with the aid of ULPs. The OR neurons in the output layer are placed to aggregate the outputs of ULPs for each corresponding consequences. In Fig. 2, the connections to the ULPs are described as bold lines which contain a set of connection lines as shown in Fig. 1. The only parameter that has to be controlled in this network is the number of ULP (NU), which will be set large enough in the experiment.

3 Experimental Results

In this paper, we consider hepatitis disease dataset available on the Machine Learning Repository site at the University of California at Irvine. It has 155 instances (32 cases of die, 123 cases of alive). This dataset has 19 input attributes (13 binary and 6 attributes with 6–8 discrete values) and 1 output attribute (die, alive) as shown in Table 1.

Table 1. Attribute information of hepatitis database

Attribute No.	Attribute	Domain
1	Age	10, 20, 30, 40, 50, 60, 70, 80
2	Sex	Male, Female
3	Steroid	No, Yes
4	Antivirals	No, Yes
5	Fatigue	No, Yes
6	Malaise	No, Yes
7	Anorexia	No, Yes
8	Liver Big	No, Yes
9	Liver Firm	No, Yes
10	Spleen Palpable	No, Yes
11	Spiders	No, Yes
12	Ascites	No, Yes
13	Varices	No, Yes
14	Bilirubin	0.39, 0.80, 1.20, 2.00, 3.00, 4.00
15	Alk Phosphate	33, 80, 120, 160, 200, 250
16	Sgot	16.: 13, 100, 200, 300, 400, 500
17	Albumin	2.1, 3.0, 3.8, 4.5, 5.0, 6.0
18	Protime	10, 20, 30, 40, 50, 60, 70, 80, 90
19	Histology	No, Yes
20	Class	Die, Alive

For the union-based fuzzy neural networks, we use 3-uniformly distributed Gaussian membership function overlapped in 0.5, and set NU=25. We select 50% of the data from the two classes evenly as random for the training and the rest 50% is used for testing. Genetic algorithms optimize binary connection weights. After that gradient-based learning further refines these optimized binary connection weights in the unit interval. The parameters used in this experiment are as follows:
GA: population size 400, generation no. 500, crossover rate 0.9, mutation rate 0.01
Gradient-based learning : learning rate 0.01, iteration no. 1000.

20 time independent simulations have been performed with different training and testing data set selected from the two classes evenly. Table 2 describes the average diagnosis rate over 20 time independent simulations. As a result of the simulation, the resulting number of rule after 20 time independent simulations is 12 to 21. As is shown in the result, the optimized union-based fuzzy neural networks have 12 to 21 rules covering most of the essential input space with reasonable diagnosis rate.

Table 2. Average diagnosis rates over 20 time independent simulations

Algorithm	Average diagnosis rate (%)	
	Training data set	Testing data set
Genetic algorithms	89.2	87.3
Gradient-based learning	91.1	90.4

4 Conclusions

This paper applied union-based fuzzy neural networks to intelligent diagnosis of hepatitis disease. Union-based fuzzy neural networks can guarantee a reduced knowledge base with subset of all possible rules by allowing union in the rule antecedent. Genetic algorithms optimized the binary connections of the union-based fuzzy neural networks, and then gradient-based learning refined the optimized binary connections in the unit interval. To show the applicability of the proposed method, we considered the hepatitis disease dataset available on the Machine Learning Repository site at the University of California at Irvine. As can be seen in the simulation results, union-based fuzzy neural networks can be successfully applied to diagnosis of hepatitis disease with a reduced number of rules.

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