The Third AFSS(1998). 296-301

Temperature Inference System by Rough-Neuro-Fuzzy Network

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Abstract

The Rough Set theory suggested by Pawlak in 1982 has been useful in AI, machine learning, knowledge acquisition, knowledge discovery from databases, expert system, inductive reasoning, etc. The main advantages of rough set are that it does not need any preliminary or additional information about data and reduce the superfluous informations. But it is a significant disadvantage in the real application that the inference result form is not the real control value but the divided disjoint interval attribute. In order to overcom this difficulty, we will propose approach in which Rough set theory and Neuro-fuzzy fusion are combined to obtain the optimal rule base from lots of input/output datum. These results are applied to the rule construction for infering the temperatures of refrigerator's specified points.

Keywords : Rough Set, Neuro-Fuzzy network, modeling, refrigerator

1. Introduction

In the past few years, the fuzzy set theory has been making a progress in the practical fields. Recently, a strong attention has focused on increasing efficiency of the fuzzy logic in the industrial application [1][6]. Neural network which possess the learning capability and is based on the parallel distributed processing can be considered as a promising technique in the area of the information processing[2][5].

Meanwhile, the fusion techniques of the above two theorys have concentrated on applying neural network to obtain the optimal rule base of fuzzy logic system [3][10]. But, unfortunately it is very hard to obtain the optimal rule base because of the limited learning capabilities of neural network.

To overcome such a difficulty, we employ some concepts of rough set theory in obtaining the optimal fuzzy rule base. Rough set theory which is proposed by Pawlak in 1982 is able to obtain the profitable informations from the uncertain and incomplete informations [9][10]. This theory does not need any preliminary and additional informations about given data. In this paper, we propose an effective Rough Fuzzy-Neural network. The proposed algorithm can construct an optimal rule base of FNN(fuzzy-neural network) system by fusing with rough set theory.

Compared with conventional FNN, the proposed approach may be considerably more realistic because it reduces the overlapping datum for constructing the rule base. In this paper, the results are applied for constructing the temperature inference system of refrigerator

The organization of this paper is as follows.

In section 2, a rule base for inferencing the inside temperature of a refrigerator is constructed by the rough set theory. And The temperature inference system by the Rough Fuzzy-Neural network is explained in Section 3. Finally, computer simulation results are shown in Section 4.

2. Construction of rule base from rough set theory

2-1. Problem statement

The conventional refrigerator control system needs a lot of sensors in order to keep the uniform distribution of the temperature. But it is not proper way to install such a lot of sensors inside the refrigerator because of the high cost and many difficulties in handling the information. One way to overcome the difficulties and obtain the effective result is to construct an efficient inference system for the interior temperatures at some specified locations.

This paper will develope an intelligent inference system for estimating the temperatures at some specified locations of the refrigerator(cf.,Fig. 1). The proposed scheme consists of the rule generation from rough set theory and the construction of the inference system by neural-fuzzy fusion.

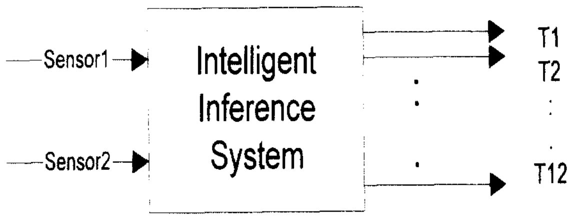


Fig. 1, Temperature inference system

2-2. Data clustering by Rough Set

In Rough Set Theory, the universal data set U is represented by the partial attribute set B in the universal attribute set A. Attribute set B induces equivalence classes which have indiscernibility relation IND(B) in the elements. We define $Reds^X(U,B)$ as a set which has the reducts of discernible attributes between the subset X in the U and the other subset(U-X) in U, and also define $Ruls^X(U,B)$ as a set which has only the minimum reducts of the subset X about an element in the subset X.

And then the whole procedure of constructing the proper rule base for inferring the temperatures at several locations of the refrigerator from rough set theory can be summarized as follows. At this time, it must be realized that there are only two sensors (c1 and c2) at some designated locations of the refrigerator and the temperatures of 12 another points must be estimated from the measuring values of two sensors.

[step 1] Rearrange the temperature values of two sensors(C1, C2), the change ratios of the sensors (dC1, dC2) and the temperature that are experimentally measured at each specified point (MBL), as shown in Table 1.

[step 2] Convert the numeric values of Table 1 into the symbolic ones as shown in Table 5 by using Table 2 ~ Table 4. (Table 5 is also called as an observation table.)

Table 1, Values of measurement

data	Sensor 1	Sensor 2	the change of Sensor 1	the change of Sensor 2	MBL
p1	2.459	2.553	-0.017	0.04	1.1
p2	2.551	2.645	-0.009	0.05	2.5
p3	2.449	2.789	-0.005	0.017	1.3
p4	2.521	2.562	-0.020	0.009	4.1
p5	2.539	2.534	-0.021	-0.040	0.2
p6	2.545	2.668	0.005	0.07	2.9
p7	2.501	2.601	-0.024	-0.008	3.9
p8	2.489	2.650	0.019	-0.041	0.1
p9	2.471	2.512	-0.029	0.09	0.2
p10	2.551	2.699	0.001	-0.039	5.7
p11	2.480	2.779	0.020	-0.044	0.5

Table 2. Attribute symbol

attribute	symbol	attribute	symbol
sensor 1	C1	MFL	d4
the change of	dC1	MFC	d5
sensor1		MFR	d6
sensor 2	dC2	LBL	d7
the change of		LBC	d8
sensor2	dC2	LBR	d9
MBL	d1	LFL	d10
MBC	d2	LFC	d11
MBR	d3	LFR	d12

Table 3. Output interval value

interval	d0~d12 attribute value
0	d(x)<0.6
1	0.6≤d(x)<2.2
2	2.2≤d(x)<3.8
3	3.8≤d(x)<5.4
4	5.4≤d(x)

Table 4. Sensor input interval value

Interval Value	C1 attribute	C2 attribute
0	C1(x)<2.460	C2(x)<2.547
1	2.460≤C1(x)<2.540	2.547≤C2(x)<2.634
2	2.540≤C1(x)	2.634≤C2(x)

Interval Value	dC1 attribute	dC2 attribute
0	dC1(x)<-0.017	dC2(x)<-0.033
1	-0.017≤dC1(x)<0.017	-0.033≤dC2(x)<0.03
2	0.017≤dC1(x)	0.03≤dC2(x)

Table 5. Observation table

data	C1	dC1	C2	dC2	d1
p1	0	1	2	2	1
p2	2	2	1	2	2
p3	0	2	1	0	1
p4	1	1	0	1	5
p5	1	0	0	0	0
p6	2	2	1	2	2
p7	1	1	0	1	3
p8	1	2	2	0	0
p9	1	0	0	2	0
p10	2	2	1	0	4
p11	1	2	2	0	0

[step 3] Simplify the observation Table 5 by reducing the overlapped row as shown in the Fig. 6. In the Table 6, C1, C2, dC1 and dC2 become the condition attributes and the temperature(i.e., d1) obtained experimentally at one of the specified points becomes the corresponding decision attribute. From Table 6, a rule can be easily obtained as follows.

IF C1 is I and C2 is J and
dC1 is K and dC2 is L , then d1 is M (1)

where I, J, K, L, and M are the discrete values of C1, C2, dC1, dC2 and d1 that are determined from Table 4.

Table 6. Reduced table

data	C1	dC1	C2	dC2	d1
u1	0	1	2	2	1
u2	0	2	1	0	1
u3	1	0	0	0	0
u4	2	2	1	2	2
u5	1	1	0	1	3
u6	1	0	0	2	0
u7	2	2	1	0	4
u8	1	2	2	0	0

[step 4] Construct the discernibility matrix M(U,B) as shown in Table 7.

$$B=\{C1, dC1, C2, dC2\}, \quad (2)$$

$$U=\{u1, u2, u3, u4, u5, u6, u7, u8\} \quad (3)$$

Table 7. Discernibility matrix M(U, B)(in part)

	u1	u2	u3	u4	u5	u6
u1		dC1, C2, dC2	C1, dC1, C2, dC2	C1, dC1 C2,	C1, C2, dC2	C1, dC1 C2
u2	dC1, C2, dC2		C1, dC1, C2,	C1, dC2	C1, dC1, C2, dC2	C1, dC1, C2, dC2
u3	C1, dC1, C2, dC2	C1, dC1, C2,		C1, dC1, C2, dC2	dC1, dC2	dC2
u4	C1, dC1 C2,	C1, dC2	C1, dC1, C2, dC2		C1, dC1, C2, dC2	C1, dC1, C2,
u5	C1, C2, dC2	C1, dC1, C2, dC2	dC1, dC2	C1, dC1, C2, dC2		dC1, dC2
u6	C1, dC1 C2	C1, dC1, C2, dC2	dC2	C1, dC1, C2,	dC1, dC2	
u7	C1, dC1, C2, dC2	C1	C1, dC1, C2,	dC2	C1, dC1, C2, dC2	C1, dC1, C2, dC2
u8	C1, dC1, dC2	C1, C2,	dC1, C2	C1, C2, dC2	dC1, C2, dC2	dC1, C2, dC2

[step 5] Find the Discernibility function from Table 7. The discernibility function can be induced as like the following example.

$$\begin{aligned} f^{u1}(U,B) &= (dC1 \vee C2 \vee dC2) \wedge (C1 \vee dC1 \vee C2 \vee dC2) \\ &\wedge (C1 \vee dC1 \vee C2) \wedge (C1 \vee C2 \vee dC2) \wedge (C1 \vee dC1 \vee C2) \\ &\wedge (C1 \vee dC1 \vee C2 \vee dC2) \wedge (C1 \vee dC1 \vee dC2) \\ &= (C1 \vee dC1 \vee C2) \wedge (dC1 \vee C2 \vee dC2) \\ &\wedge (C1 \vee C2 \vee dC2) \wedge (C1 \vee dC1 \vee dC2) \\ &= (C1 \wedge dC1) \vee (dC1 \wedge dC2) \vee (C1 \wedge C2) \vee (C2 \wedge dC2) \end{aligned} \quad (4)$$

[step 6] Define a subset $X=\{x \in U | d1(x)=d1_1\}=\{u1, u2\}$ in the set U, and find the corresponding reducts of u1, u2 by simplifying discernibility functions as follows.

$$\mathrm{Reds}^{u1}(U-\{u_2\},B) = \{\{C1\},\{dC1,C2\},\{dC1,dC2\},\{C2,dC2\}\} \quad (5)$$

$$\mathrm{Reds}^{u2}(U-\{u_1\},B) = \{\{C1\}\} \quad (6)$$

$$\mathrm{Reds}^{X}(U,B) = \{\{C1_0\},\{dC1_1,C2_2\},\{dC1_1,dC2_2\},\{C2_2,dC2_2\}\} \quad (7)$$

[step 7] Obtain the reducts for X that can cluster the universe data set U and then find the corresponding rules by selecting the minimum reducts from each element u1 and u2 as follows.

$$\mathrm{Ruls}^{X}(U,B) = \{\{C1_0\}\} \quad (8)$$

[step 8] Determine the corresponding rule from Eq.(8) as follows.

$$\text{IF } C1=0, \text{ then } d1=1 \quad (9)$$

3. Intelligent Temperature Inference system

3.1 System structure

Generally, the rule base that is determined from rough set outputs the interval discrete value. This fact limits the application of the rule base obtained from rough set theory because, in many applications, the practical real values are required. Furthermore, in case of inconsistent rules (which means that the rules outputs the different results from the same condition attributes), the accuracy of the inferred values has some limitations. Thus it caan be easily realized that one way to overcome the problems is to combine the rough set theory and neural-fuzzy technique as shown in Fig. 2.

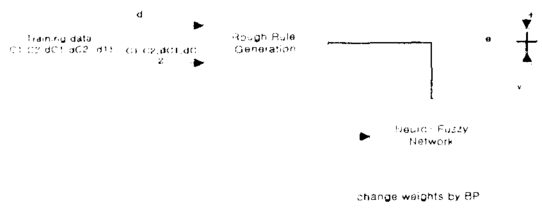


Fig. 2, The structure of the rough neuro-fuzzy system

3-2. Inference System for Temperature using Rough-Fuzzy-Neural Networks

Suppose that a rule at a refrigeration point is given as follows..

$$\textit{IF } C1 \textit{ is } N \text{ and } C2 \textit{ is } Z \text{ and } dC1 \textit{ is } Z \text{ and } dC2 \textit{ is } P, \textit{ then } dI = Y \quad (10)$$

where N, Z, and P are the discrete values represented by membership functions in the Fig. 3.

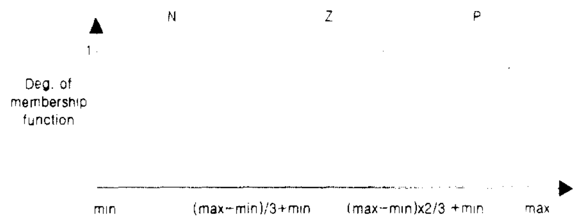


Fig. 3, Rough membership function

Since the membership functions are discrete, the inferred output can not be applied to the real system. Thus it is necessary to transform rough membership functions into fuzzy membership functions (Fig. 4) and the consequent interval values are transformed to a real intermediate value of intervals as follows.

$$\textit{IF } C1 \textit{ is } N \text{ and } C2 \textit{ is } Z \text{ and } dC1 \textit{ is } Z \text{ and } dC2 \textit{ is } P, \textit{ then } d1 = a \quad (11)$$

where N, Z, and P are fuzzy membership functions shown in Fig. 4 and a is the real intermediate value of an interval Y. Then the fuzzy rules can be reconstructed by the fuzzy-neural network as shown in the Fig. 5

In the Fig. 5, we can infer an output y, which represents the temperature of a point in the refrigerator, from the sensors(C1, C2) and their change ratios(dC1, dC2). Furthermore we can adjust the membership degree of condition input (C1,C2,dC1,dC2) by the following learning algorithm.

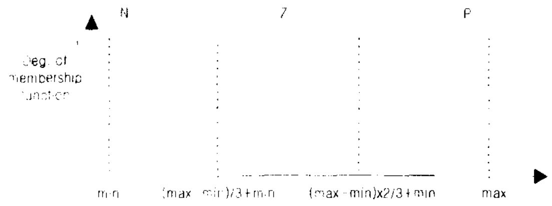


Fig. 4, Fuzzy membership function

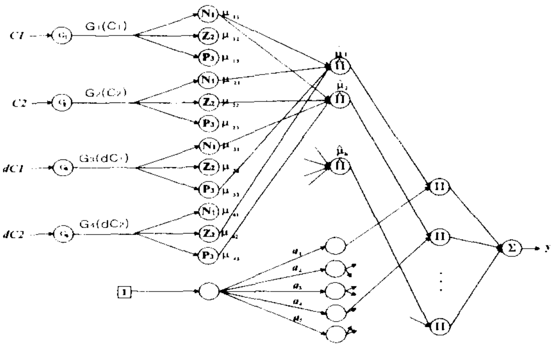


Fig. 5, Neuro-fuzzy network structure

The procedure of the inference of the neural network shown in Fig. 5 can be summarized as follows.

$$\mu_{ij} = A(G_i(x)) \qquad (i=0,2,3,4) \quad (12)$$

$$A(x) = \begin{cases} 1 - \dfrac{2|x - c_A|}{w_A}, & 2|x - c_A| < w_A \\ 0 & , \textit{otherwise} \end{cases} \quad (13)$$

$$\widehat{\mu_j} = \frac{\prod_{k=0}^{3} \mu_{kj}}{\sum_{k=0}^{m} \mu_k} \quad (14)$$

where x is the input value of sensor and the A(·) represents fuzzy membership function. Also C_A and W_A represents the center and width of membership functions, respectively. The final inference value can be determined as follows.

$$y = \frac{\sum_{j=0}^{m} \mu_j \cdot a_j}{\sum_{j=0}^{m} \mu_j} = \sum_{j=0}^{m} \widehat{\mu_j} \cdot a_j \quad (15)$$

Meanwhile the learning procedure of the network can be explained by defining an error function in order to adjust parameters a_i (which is the decision weights of neuro-fuzzy network in the Fig. 5) as follows.

$$E(t) = \frac{1}{2}\,(\,d_0(t) - y_0(t)\,)^2 \quad (16)$$

$$\Delta a_j = -\eta \cdot \frac{\partial E}{\partial a_j} = -\eta \cdot \frac{\partial E}{\partial y_i} \cdot \frac{\partial y_i}{\partial f_j} \cdot \frac{\partial f_j}{\partial a_j}$$

$$= \eta \cdot (\,d_i - y_i\,) \cdot \widehat{\mu_j} \quad (17)$$

$$a_j(t+1) = a_j(t) + \Delta a_j(t) \quad (18)$$

The parameters a_j are updated with the Δa_j of Eq.(17) and Eq.(18) to minimize the error function defined by Eq.(16).

4. Computer Simulation

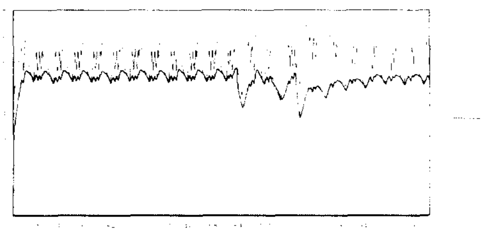


Fig. 6, Inputs of sensor 1, sensor 2

In Fig. 6 , the input values of sensor C1 and C2 are partly shown for explanation of computer simulation. And the minimum reducts can be obtained by the following equation.

$$\text{Ruls}^{\overline{B}X}(U,B) \quad (19)$$

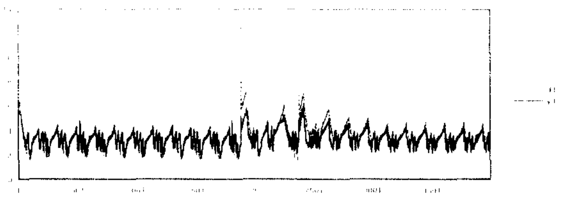
U : reduced data set(d1, . . . , d12)

B : C1, dC1, C2, dC2

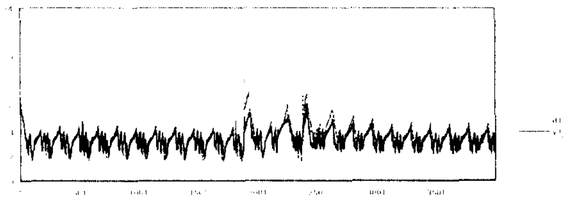
Using Eq.(12), we can obtain the rules for d1. The induced rules are shown partly in Table 8.

Table 8. The part of generated MBL(d1) rule

C1	C2	dC1	dC2		d1
0	0	-	-	⇒	4
-	1	0	-	⇒	4
0	1	1	-	⇒	4
1	0	0	-	⇒	4
1	0	1	1	⇒	4
1	1	1	1	⇒	4
0	-	1	1	⇒	3
	⋮	⋮	⋮		



(a) Inference with Rough-Fuzzy Rule
(RMS error = 0.2211)



(b) After learning
(RMS error = 0.1926)

Fig. 7. Inference result

Fig. 7(a) shows one of the inference results obtained from only the rough-fuzzy rules of Table 8. Also Fig. 7(b) shows the inference result after learning of the fuzzy-neural network. It can be realized from these results that the error between the inferenced result and the measured one has been decreased through iterative learning and the proposed scheme becomes very effective in estimating the real temperatures at some specified locations of the refrigerator.

5. Conclusion

An effective scheme to estimate the temperatures of the several locations inside a refrigerator has been proposed in this paper. Especially, this scheme has the distinct advantages to overcome the limitation of the rough set theory in real applications.

Reference

1. E. Czogala, A. Mrozek, Z. Pawlak, "The idea of a rough fuzzy controller and its application to the stabilization of a pendulum-car system," Fuzzy Sets and Systems 72, pp. 61-73, 1995.
2. E. Czogala, "On the Modification of Rule Connective in Fuzzy Logic Controllers Using Zimmermann's Compensatory Operators," EUFIT 93 September 7-10, Aachen(Germany), pp. 1329-1333, 1993.
3. R.Yasdi,"Combining Rough Sets Learning and Neural Learning-method to deal with uncertain and imprecise information", Neurocomputing 7, pp. 61-84, 1995.
4. S. Horikawa, T. Furuhasi, S. Okuma, Y. Uchikawa, "On fuzzy modelling using fuzzy neural networks with the back-propagation algorithm," IEEE Trans. on neural network, vol. 3, no. 5, pp. 801-806, 1992.
5. C.C. Lee, "An intelligent Control Based on Fuzzy Logic and Neural Network Theory," Proc. of the Int. Conf. on Fuzzy Logic and Neural Network(IIZUKA 90), pp. 756-764, 1990.
6. P. Lingras, "Rough Neural Networks," Tech. Memo 117-106, Algoma Univ., Canada, 1995.
7. A. Mrozek, "Information systems and control algorithms," Bull Polish Academy Sci. T. Sc. 33, pp. 195-204, 1985.
8. A. Mrozek, "Use of rough sets and decision tables for implementing rule-based control of industrial processes," Bull. Polish Academy Sci. T. Sc. 34, pp. 357-371, 1986.
9. Z. Pawlak, "Rough sets" Int. J. Inform. Comput. Sci. 11, pp. 341-356, 1982.
10. Z. Pawlak, "Rough sets: Theoretical Aspects of Reasoning About Data," Kluwer Academic Publisher, Dordrecht Boston London, 1991.