The Application of Tolerant Rough Set Neural Network to Fighter Fault Diagnosis

Guoqiang Sun[1,2], Hongli Wang[1]
[1]The Second Artillery Engineering University
Xi’an, China
e-mail: sun7451@163.com, wanghl@163.com

Jun Tao[2], Xubing Li[2]
[2]Aviation University of Air Force
Changchun, China
e-mail: 980626918@qq.com cicelyli@yahoo.com.cn

***Abstract*—Conventional rough set theory is based on indiscernibility relation, which lacks the adaptive ability to data noise or data missing. Furthermore, it may present qualitatively whether or not the faults exist, but it can’t compute accurately the value of the faults. Though the neural network has ability of approximating unknown nonlinear systems, but it can’t distinguish the redundant knowledge from useful knowledge, so it’s classification ability can’t catch up with the rough set classifier. This paper combines the rough set theory and the tolerant rough set neural network to diagnose the rudder faults of fighter, which solves well the problem of fault diagnosis and fault degree computation. Simulation results demonstrate the effectiveness of the proposed method.**

Keywords- Rough Set; Tolerant Relation; Fault Diagnosis; Neural Network

I. INTRODUCTION

Rough set theory proposed by Pawlak is based on indiscernibility relation [1], which is a strict equivalence relation. In some actual problems, Rough set theory lacks the adaptive ability to data noise or data missing. In order to extend the application range, Ziarko proposed a variable precision rough sets(VPRS) Approach [2], Dubois proposed a fuzzy rough sets method [3]. Furthermore, many rough sets algorithm based on tolerant relation were proposed [4-5].

Artificial Neural Network as a pattern recognition technique shows great potential for application in the field of equipment fault diagnosis [6-7]. Though the neural network has ability of approximating unknown nonlinear systems [8], but it can’t distinguish the redundant knowledge from useful knowledge, so it’s classification ability can’t catch up with the rough set classifier. Rough set classifier may present qualitatively whether or not the faults exist, but it can’t compute accurately the value of the faults. The tolerant relation rough set neural network builded by regarding rough set membership function under tolerant relation as roughness factor can diagnose the size of fault degree.

This paper combines the rough set theory and the tolerant rough set neural network to diagnose the rudder faults of fighter, which solves well the problem of fault diagnosis and fault degree computation. Simulation results demonstrate the effectiveness of the proposed method.

II. TOLERANT ROUGH SET

Let $A=(U, A\cup d)$ be a decision table [9]. Here, U is a set of elements (objects, examples), A is a set of condition attributes, where each attribute $a\in A$ has a set of attribute values V_a , and the set $\{d\}$ is a decision set such as $d=\{1,2,3,\cdots,r(d)\}$, where $r(d)$ is a number of decision classes. Let $R_a=\{R_a : R_a \subseteq V_a \times V_a \wedge a\in A\}$ is a set of tolerant relations. Then each such a tolerance relation satisfies

reflexive: $\forall v_1 \in V_a, v_1 R_a v_1$,

symmetric: $v_1 R_a v_2 \to v_2 R_a v_1$,

where v_1 and v_2 are some attribute values in V_a. We say that two objects x and y are similar to with respect to the attribute a when the attribute values $a(x)$ and $a(y)$ satisfy $a(x)R_a a(y)$. Further, we say that two objects x and y are similar with respect to all attributes A, when they satisfy the tolerance relation with respective to all attributes, i.e. $\forall a\in A$, $a(x)R_a a(y)$. Hereafter, we denote the above similarity between two objects x and y with respect to all attributes A as $x\tau_A y$ in order to emphasize the tolerance relation.

Definition 1[10] Given any $x,\tilde{x}\in U$, $B\subseteq C$, let tolerant relation N is

$$xN_B^{\delta}\tilde{x}=\{(x,\tilde{x})\in U\times U : |f(x,a)-f(\tilde{x},a)|\le\delta\cup|d(x)-d(\tilde{x})|\le\delta,\forall a\in B\}$$

Where, $\delta\ \ge 0$, and called $(x,\tilde{x})$ δ degree tolerance under properties B , denoted $\delta\sim(B)$ - tolerance.

Definition 2[10] If $(x,\tilde{x})$ is $\delta\sim(B)$ -tolerance, the tolerant extent of them is measured with the following formula

$$\tau(x,\tilde{x})=w_c\Big(\frac{s}{\|B\|}+\frac{1}{\|B\|}\Big(\sum_{\forall a\in B}\frac{|f(x,a)-f(\tilde{x},a)|}{\max(f(i,a))}\Big)\Big)+w_d\Big(1-\frac{d(x)-d(\tilde{x})}{\max(d(i))}\Big)$$

Where, i is of all individuals, w_c and w_d were the relative importance of the condition attributes and decision attributes, $0\le w_c, w_d\le 1$, and $w_c+w_d=1$. s is the number of properties a under $f(x,a)-f(\tilde{x},a)=0$, $|\bullet|$ expresses the absolute, $\|\bullet\|$ expresses Cardinal number.

Definition 3[10] Let $x \in U, X \subseteq U$, Consider the degree x belong to X under tolerant relation

$$\mu_X{}^N(x) = \frac{card([x]_{N,T}^1 \cap X)}{card(X)}$$

is rough membership function based on tolerant relations. Where, $card(S)$ expresses cardinality of S .Obviously, $\mu_X{}^N(x) \in [0,1]$.

III. Design of Rough Set Neural Network Based on Tolerant Relation

As the rough set theory itself, the lack of redundancy of data noise, while the neural network can improve the learning and generalization ability. Therefore, the rough membership function is applied to the design of the neurons, for training the neural network model, can be a good solution to the problem of pattern recognition. The steps of the method are as follows:

(1) Extract all kinds of sample data required and express as knowledge system S ;

(2) discrete processing of knowledge system S using equifrequent method;

(3) Calculate the tolerant degree of each sample point with the sample point of the various kinds of sample data set. Calculate rough membership degree $\mu_X^\tau(\chi)$ of each sample point with the different data sets according to the definition (3);

(4) Design of BP neural network: input vector dimension depends on the number of sample properties, the dimension of the output vector depends on the number of pattern recognition data set. The number of hidden layers and the number of hidden layer neurons are determined according to the actual needs. Hidden layer activation function is the following formula

$$f(z) = \frac{1}{1+e^{-z}}$$

(5) Take $\mu_X^\tau(\chi)$ obtained from (3) into the neural network. If $\mu_X^\tau(\chi)$ is brought into the output layer, the activation function is $f^R(z) = \mu_X^N(\chi) * f(z)$, where $f(z) = a*z+b$, b is the threshold, f is the activation function of neurons;

(6) Stable weights and threshold obtained using the steepest descent method after several iterations of training;

(7) Re-extracting with each 5% of the value range of the random noise and fault data as the test set, and processed into a knowledge system in the form of S ;

(8) Repeat steps (2) and (3), calculate tolerance relation rough membership function value of each individual with either a fault in this case;

(9) Calculate the neuron output value of the test set using he weights and threshold values obtained in step (6) and rough membership function value in step (8). The value 1 indicates that the neuron corresponding to the fault occurs, the value 0 indicates that the neurons corresponding failure did not occur.

IV. Fighter Fault Diagnosis Based on Rough Set Classifier

The data comes from a nonlinear aircraft model output data. Set aircraft flight altitude of 5,000 meters, the flight Mach 0.6, set the sampling time of 0.012 seconds.

Construct the decision table $S = (U, A)$, which U indicates a different fighter structural fault state;, $A = C \cup D$, $C = \{c_1, c_2, \cdots, c_7, c_8\}$ indicates the condition attributes, which are defined as the attack angle (α), sideslip angle (β), roll angular rate (W_x), pitch angular rate (w_z), yaw angular rate (w_y), yaw angle (ψ), pitch angle (θ) and roll corner (γ); $D = \{D_0, D_1, \cdots, D_5\}$ indicates the decision attributes, which are defined as trouble-free, aileron stuck, the aileron injury, Horizontal tail stuck, Horizontal tail injury and rudder damage. Collection of normal and fault data of 240 states, a decision table in Table Ⅰ.

TABLE I. Decision Table

State	α	β	W_x	W_z	W_y	ψ	θ	γ	**D**
1	5.1418	0.0000	0.0000	0.0003	0.0000	0.0000	5.1051	0.0000	0
…	…	…	…	…	…	…	…	…	0
40	5.1148	0.0000	0.0000	-0.0002	0.0000	0.0000	5.0872	0.0000	0
41	5.0917	-0.0117	-0.3941	0.0925	0.1856	0.1288	5.0774	-0.0023	1
…	…	…	…	…	…	….	…	…	1
80	5.0927	0.0112	0.4165	0.0965	-0.2018	-0.1308	5.0618	-0.0023	1
81	5.1401	0.0116	0.0901	0.0599	-0.1876	-0.3978	4.5441	0.0029	2
…	…	…	…	…	…	…	…	…	2
120	5.1098	0.0106	0.1268	0.0652	-0.1988	-0.3395	4.5855	0.0030	2
121	5.1426	0.0160	1.4531	0.1437	-1.9991	-0.4736	5.0457	0.0132	3
…	…	…	…	…	…	…	…	…	3
160	5.1156	-0.0044	1.3108	0.5247	-1.4371	-0.0929	4.9727	-0.0195	3
161	5.1110	0.0783	5.4772	0.7263	-2.1615	-0.2637	5.0366	0.0412	4
….	…	…	…	…	…	…	…	…	4
200	5.1403	-0.3280	1.8899	1.2969	-0.1439	-0.0053	5.0457	0.2010	4
201	5.1209	0.0000	0.0000	0.0028	0.0000	0.0000	5.0448	0.0000	5
…	…	…	…	…	…	…	…	…	5
240	5.1191	0.0000	0.0000	0.0027	0.0000	0.0000	5.0435	0.0000	5

Table Ⅰ discretization based on the improved greedy algorithm [11] proposed by S.H.Nguyen to get the discrete decision table, shown in TableⅡ. TableⅢ is the table of discretization decision table including noise.

TableⅡ reduction method based on the reduction of the genetic algorithm, following rules set:

α (1) AND w_x (0) AND w_z (1) => D (5)

α (2) AND w_x (0) AND w_z (1) => D (5)

α (2) AND w_x (1) AND w_z (3) => D (4)

α (0) AND w_x (1) AND w_z (3) => D (4)

α (1) AND w_x (1) AND w_z (3) => D (4)

α (1) AND w_x (0) AND w_z (3) => D (3)

α (2) AND w_x (0) AND w_z (3) => D (3)

α (0) AND w_x (0) AND w_z (2) => D (2)

α (1) AND w_x (0) AND w_z (2) => D (2)

α (2) AND w_x (0) AND w_z (2) => D (2)

α (0) AND w_x (0) AND w_z (3) => D (1)

α (0) AND w_x (0) AND w_z (0) => D (0)

α (2) AND w_x (0) AND w_z (0) => D (0)

TABLE II. DISCRETIZATION DECISION TABLE

State	α	β	W_x	W_z	W_y	ψ	θ	γ	D
1	2	0	0	0	0	0	0	0	0
…	…	…	…	…	…	…	…	…	0
40	0	0	0	0	0	0	0	0	0
41	0	0	0	3	0	0	0	0	1
…	…	…	…	…	…	….	…	…	1
80	0	0	0	3	0	0	0	0	1
81	2	0	0	2	0	0	0	0	2
…	…	…	…	…	…	…	…	…	2
120	0	0	0	2	0	0	0	0	2
121	2	0	0	3	0	0	0	0	3
…	…	…	…	…	…	…	…	…	3
160	1	0	0	3	0	0	0	0	3
161	0	0	1	3	0	0	0	0	4
….	…	…	…	…	…	…	…	…	4
200	2	0	1	3	0	0	0	0	4
201	2	0	0	1	0	0	0	0	5
…	…	…	…	…	…	…	…	…	5
240	1	0	0	1	0	0	0	0	5

TABLE III. DISCRETIZATION DECISION TABLE INCLUDING NOISE

State	α	β	W_x	W_z	W_y	ψ	θ	γ
1	0	0	0	0	0	0	0	0
…	…	…	…	…	…	…	…	…
40	2	0	0	2	0	0	0	0
41	0	0	0	3	0	0	0	0
…	…	…	…	…	…	….	…	…
80	0	0	0	3	0	0	0	0
81	2	0	0	2	0	0	0	0
…	…	…	…	…	…	…	…	…
120	1	0	0	2	0	0	0	0
121	0	0	0	3	0	0	0	0
…	…	…	…	…	…	…	…	…
160	2	0	0	3	0	0	0	0
161	2	0	1	3	0	0	0	0
….	…	…	…	…	…	…	…	…
200	1	0	1	3	0	0	0	0
201	1	0	0	1	0	0	0	0
…	…	…	…	…	…	…	…	…
240	1	0	0	0	0	0	0	0

Obtained above was the use of the rule set for fault diagnosis, diagnosis results are shown in Table Ⅳ.

TABLE IV. OUTCOME TABLE OF FAULT DIAGNOSIS

	Identification number	**Correct number**	**Error number**	**No identification number**	**Accuracy**	**Recognition rate**
0	40	34	6	0	0.85	1.0
1	40	40	0	0	1.0	1.0
2	40	40	0	0	1.0	1.0
3	40	33	7	0	0.83	1.0
4	40	40	0	0	1.0	1.0
5	30	30	0	10	1.0	0.75
Total	230	220	10	10	0.96	0.95

V. SECONDARY TRAINING AND SIMULATION OF TOLERANT ROUGH SET NEURAL NETWORK FAULT DEGREE SIZE

Rough set classifier can diagnose the type and location of the fault, rough set classifier can not be accurately calculated the size of the fault degree. Therefore, we diagnose the type and location of the fault using the rough set classifier, and then perform secondary training of fault degree size adopting tolerant relation rough set neural network to further diagnose the size of the fault degree.

Horizontal tail damage, for example, shows the application of tolerant rough set neural network (RNN) to failure secondary diagnosis. Input is 8-dimensional vector, and the output is 3-dimensional vector (corresponding to the three kinds of different fault size, such as some kind of failure occurs, the corresponding position output to 1, and the other is 0, the fault types and corresponding network output seen in TableⅤ), the network includes a hidden layer, the number of neurons is 10.

TABLE V. OUTCOME TABLE OF TAIL PLANE FAULT

Fault type	**Network output**
20%	[y1 0 0]
50%	[0 y2 0]
100%	[0 0 y3]

50 times training simulation results compare of 50% test samples and 100 times training simulation results compare of 50% test samples plus disturbance are as follows.

TABLE VI. 50 TIMES TRAINING SIMULATION RESULTS COMPARE OF 50% TEST SAMPLES

	RNN	**ANN**
20% relative error of fault degree (%)	0	0
50% relative error of fault degree (%)	0	5.5
100% relative error of fault degree (%)	0	0
relative error of the whole system (%)	0	1.83

TABLE VII. 100 TIMES TRAINING SIMULATION RESULTS COMPARE OF 50% TEST SAMPLES PLUS DISTURBANCE

	RNN	**ANN**
20% relative error of fault degree (%)	0	6.5
50% relative error of fault degree (%)	27.5	37.5
100% relative error of fault degree (%)	0	0
relative error of the whole system (%)	7.9	14.7

We can easily see from the simulation results that the output accuracy of the tolerant rough set neural network is higher than that of the BP neural network under the same conditions, as shown in TableⅥ. As can be seen from Table Ⅶ, test comparison was performed when the training data plus disturbance signal, the output accuracy of the tolerant rough set neural network is higher than that of the BP neural network, which shows that the generalization ability of the tolerant rough set neural network is higher than that of the BP neural network.

VI. CONCLUSION

Firstly, this paper estimates the type and the position of a certain type of fighter failure using rough set classifier. Then it diagnose the value of the fault degree based on the secondary fault diagnosis of the tolerant rough set neural network and analogy the accuracy and generalization ability of them. Simulation results illustrate the output accuracy and the generalization ability of the tolerant rough set neural network is significantly better than that of the BP neural network.

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