Complex Maneuverable Events Detection Based On REFNN

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***Abstract*—In this paper, a method based on REFNN (Rough-Evolution Fuzzy Neural Network) is proposed to deal with such problems as imprecision and poor real-time performance in complex maneuverable events detection. Firstly, the optimal discrete values of continuous attributes are obtained through GA (Genetic Algorithm); secondly, the minimal rule sets from data samples are acquired by using the Rough Set Theory; then, these rules are used to construct the initial scalar values of neural cells in each layer and their relative parameters in the fuzzy neural network; lastly, parameters of the network are acquired by using BP(back propagation) algorithm. The simulation shows the effectiveness of the new method of complex maneuverable events detection based on REFNN; simultaneously REFNN has structure advantages.**

***Index Terms*—situation assessment, complex maneuverable events, events detection, REFNN**

I. INTRODUCTION

In battlefield situation assessment, events detection plays an important role in each inference layer. It's the perception of current battlefield information and is also the basis of situation assessment[1-2]. However, events in a battlefield are complex and changeful, frequent and vague because of the complexity of battlefield situation and the diversity of combat platforms and their great maneuverability. All these lead to great difficulties in events detection and identification. Complex maneuverable events are currently detected mainly by fuzzy logic and fuzzy neural network. References[3-5] have proposed a method based on fuzzy logic to detect events in battlefield, the method has good real-time performance and is effective to detect the simple battlefield events, but it has poor accuracy to detect the complex maneuverable events. Hence, the method can't meet the requirements for situation assessment in complex and changeful battlefield environment. Reference[6] use IFNN(Intuitionistic Fuzzy Neural Network) to make researches on the complex maneuverable events in air combat. Nevertheless, IFNN has complex construction and many rules, therefore, the real-time performance and the effectiveness of certain complex maneuverable events detection are still not ideal.

Therefore, in this paper, a method based on REFNN (Rough-Evolution Fuzzy Neural Network) is proposed to deal with the defects of fuzzy logic and FNN in complex maneuverable events detection. Firstly, the optimal discrete values of continuous attributes are obtained through GA (Genetic Algorithm); secondly, the unimportant rules(the degree of support of rules is too low) are removed and the minimal rule sets from data samples are acquired by using the rough set theory; then, these rules are used to construct the initial scalar values of neural cells in each layer and their relative parameters in the fuzzy neural network; lastly, parameters of the network are acquired by using BP algorithm. Compared with the proposed method in reference[7], REFNN method can make full use of all the characteristics of the sample data to reduce the number of rules, simplify network structure, improve the precision of detection and the real-time performance.

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II. TACTICS MANEUVERABLE EVENTS OF TARGETS

In a complex battlefield environment, multiple-batch and frequent maneuver of targets usually lead to explosive changes in their information. In order to perceive battlefield changes reasonably so as to give strong support to situation assessment system, the events, which are meaningful to situation assessment and higher levels of information fusion should be extracted immediately from massive changeful information of battlefield situation. This makes the compression and extraction of useful information data extremely important and critical. Maneuverable events of targets in air combat have special significance and practical influence on the situation changes. They are the combination of various state changes of aircrafts, which mainly complete some special tactical movements. Tactical maneuverable events include the following:

(1) Climbing: aircraft converts kinetic energy into potential energy, increasing height gradually, and speed becomes slower. Tactical aim: to ease the brake (brake).

(2) Accelerated climbing: a maneuverable flight of aircraft, in which the aircraft climbs rapidly upward and increases speed gradually. Tactical aim: to pursue and attack aerial targets or to occupy a high and favorable position.

(3) Hovering: a curve motion of aircraft, in which the aircraft, while retaining the same speed, curves within a horizontal plane. Tactical aim: to occupy the favorable position or to achieve a strong advantage in counterattack.

(4) Horizontal steering: in a certain period of time, the speed and height of the aircraft are almost the same as previous, with only transient direction changes in the horizontal motion of the aircraft. Tactical aim: to get away from being tailed or to maintain the advantage in dogfight.

(5) Emergency steering: aircraft flies in a 180° turn and increases the speed all the time. Tactical aim: to quickly get away from being tailed and to use the maximum steering speed to turn against the attacker.

(6) Diving: by converting potential energy into kinetic energy the aircraft flies downward along a track which forms a 30° plus angle with the horizontal plane, so that it obtains a larger speed. Tactical aim: to obtain a high speed to get out of danger or to attack the ground targets.

Tactical maneuverable events are the combination of regular changes of many state parameters, indicating that target wants to achieve its intent to implement a tactical combat action, which will affect the evolution of the air battlefield situation. Due to the sensors' perception error of the targets' state, plus the complicated battlefield situation, there is little regularity in the targets' movement, so that a strong ambiguity and uncertainty can exist in a variety of tactical events.

III. REFNN DETECTION MODEL

The basic idea is as follows: firstly, establish the sample data table; secondly, use GA algorithm to discretize continuous attribute values; thirdly, use the rough set theory to reduce the condition attribute values; then extract rules from the decision table to determine the initial fuzzy neural network topology; finally, use the original data to train the network and adjust its structure, and thus the optimal maneuverable events detection model is obtained (see Figure 1).

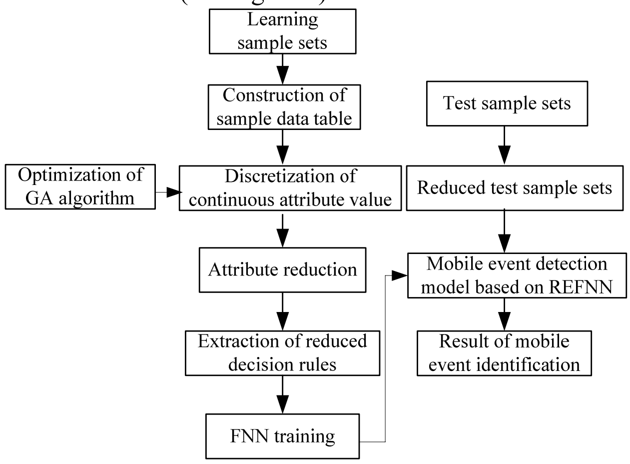

Figure 1. REFNN Detection Model

A. The Establishment of Sample Data Table

Rough set theory is established on the basis of equivalence classes, the main idea is to use known knowledge base to approximately depict the inexact or uncertain knowledge[8]. In the multiple-input-single-output(MISO) system , using m sets of samples to construct the data table $S=\langle U,X,Y,V,f\rangle$, in which $U=\{u_1,u_2,\cdots,u_m\}$ is the set of objects, each U_j is called a goal; If $X\bigcup Y=R$ is the set of attributes, and $X\bigcap Y=\varnothing$, then $S=\langle U,X,Y,V,f\rangle$ is called the decision table, $X=\{x_i\}$ is the condition attribute set (input variables), $Y=\{y\}$ is the decision attribute set (output variables), a single attribute can be viewed as one equivalent relation; $V=\bigcup_{r\in R} V_r, V_r$ is the range of attribute r ; $f:U\times R\to V$ is the information function, which specifies the attribute value of each target x , $\forall r\in R, u\in U, f(u,r)\in V_r$. When V, f is clearly known, abridged notation of the decision table $S=\langle U,X,Y,V,f\rangle$ can be $S=\langle U,R\rangle$.

B. Discretization of Continuous Attributes

Fuzzily discretize the condition attribute value. Set attribute $x_i\in[x_{i\min},x_{i\max}]$. Divide the attribute values $x_i\in[x_{i\min},x_{i\max}]$ into m_i equal parts. Then each equal-division point corresponds to a fuzzy set. The membership function value of the point is 1. Fuzzy membership function is taken to be triangular. Set the value of attribute x_i to be x_{ij}, and make

$$\mu_{A_i}(x_{ij})=\max_{k\in\{1,2,\cdots,m_i\}}\{\mu_{A_{ik}}(x_{ij})\} \quad (1)$$

A_{ik} is the fuzzy subset of x_i in the formula. It also corresponds to k, one of x_i's discrete attribute values. Select the discrete attribute values to which the fuzzy subset of the x_{ij}'s maximum fuzzy membership function value corresponds as the discrete values of x_{ij}.

Discretize the decision attribute values by equal intervals. Define decision attribute $y = [y_{\min}, y_{\max}]$. Divide $[y_{\min}, y_{\max}]$ into n_i equal parts. The equal-division point is y_l. Set decision attribute value as y, then y_k will be obtained, that is

$$|y - y_k| = \min_{l \in \{1,2,\cdots,n_i\}} \{|y - y_l|\}, k \in (1,2,\cdots,n_i) \quad (2)$$

When all the attribute values are discretized, replace the continuous attribute values with the discrete ones. So we obtain a discrete information table. Each discrete data sample in the table can be regarded as a rule, confidence level of the rule is defined as:

$$\mu_j = \prod_{i=1}^{n} \mu_{A_i}^{(j)}(x_{ij}) \quad (3)$$

j is the j_{th} rule in the formula, $j = 1,2,\cdots,m$.

The degree of discretization of continuous attributes significantly affects the performance of the network. From the perspective of rough set theory, if discrete interval is too large, then it's likely to miss important attributes, and if discrete interval is too small, then it's easy to get inconsistent decision tables, and also difficult to achieve attributes of simplicity. From the perspective of neural networks, if discrete interval is too large, then REFFN network structure will be too small, and if discrete interval is too small, then REFFN network structure will be too large. Theory and simulation have confirmed that the large network structure will lead to over-fitting the data for learning, generalization is poor; the small network structure will difficult to learn sample data. Hence, how to get the optimal discrete values of input-output attributes is the key to design REFNN with excellent performance. In this paper, GA algorithm is used to find the optimal discrete values.

Coding

Binary coding is used. The discrete scope of each variable is set to be 2~9, 3-digit binary is used to express values from 000 to 111. Suppose there are a total of 6 input-output variables $(x_1, x_2, x_3, x_4, y_1, y_2)$, then the binary strings: 011, 010, 001, 101, 100, 000 respectively indicate that the partition number of x_1 is bin2dec (011) +2 = 5, (bin2dec ( ) is a function which converts a binary string into a decimal number). Similarly, the partition number of x_2 is 4, the partition number of x_3 is 3, the partition number of x_4 is 7, the partition number of y_1 is 6, and the partition number of y_2 is 2. So the discretization degree of input-output is recorded as [5 4 3 7 6 2].

Fitness Function

Each chromosome (binary string) corresponds to a fuzzy neural network. The generalization result $J(s)$ of the neural network is used to construct a fitness function which measures the fitness degree of a chromosome. Set the fitness function $f(s) = 1/J(s)$, in which s is a binary string, $J(s)$ indicates the generalization results of the neural network to which the binary string corresponds. $J(s)$ is defined as follows:

$$J(s) = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}[y_i - y_i']^2} \quad (4)$$

$$(x_i, y_i) \in S_{test}$$

In the formular: $S_{test} = \{(x_i - y_i), i = 1,2,\cdots,N_t\}$ is the test sample sets; N_t is the test sample number; y_i is the actual value; y_i' is the output of neural networks.

Evolutionary Process

Firstly, generate random initial population. Calculate, within the initial population, each individual's fitness value. Then obtain the breeding population through competitive strategies of survival. That is, choose two individuals randomly from the initial population. The individual with a greater fitness value will join the breeding population with probability P_s. The individual with a smaller fitness value will join the breeding population with probability $1 - P_s (0.5 < P_s < 1)$. Then loop the following steps (Evolution process is shown in Fig. 2):

(1) Perform a crossover operation, with probability P_c, on two random individuals from the breeding population;

(2) With probability P_m, mutate the chromosomes obtained in step (1);

(3) Calculate the fitness values of the obtained chromosomes;

(4) Substitute the obtained chromosomes for the two individuals which have the minimal fitness values in the initial population;

(5) Following the strategies of competitive survival, select another two individuals from the initial population to join the breeding population, replacing the two individuals that have already reproduced in the cycle;

(6) If the termination criterion is met, then terminate; otherwise go back to step (2);

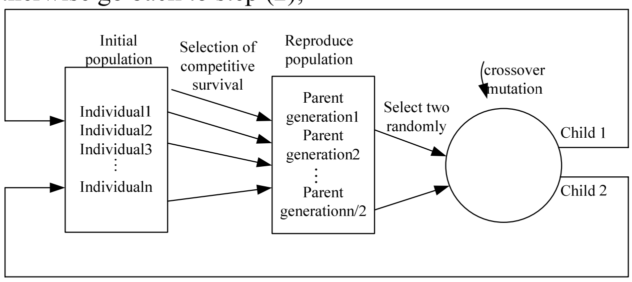

Figure 2. Evolution Process

Termination Criterion

When the fitness degree of the generated individual reaches the intended value, or when the number of iterations reaches a predetermined value, the evolutionary process will terminate.

C. Attribute Reduction

Set U as a non-empty finite set, $P = \{R_1, R_2, \cdots, R_m\}$ is the equivalence relation family (attribute set) of U, then relation system $K = (U, P)$ is called knowledge base. j is the j_{th} rule, $j = 1,2,\cdots,m$. Set the knowledge base $K = (U, P)$, $ind(K)$ is the set which is constructed by all equivalence relation in K. To each sub-set $Z \subseteq U$ and a equivalence relation $R \in ind(K)$, $\underline{R}(Z) = \{u \in U \mid [u]_R \subseteq Z\}$ is called the lower approximation of Z, and $\overline{R}(Z) = \{u \in U \mid [u]_R \cap Z \neq \varnothing\}$ is called the upper approximation of Z.

Set X and Y as the equivalence relation families of U. The positive region X of Y is recorded as $pos_X(Y) = \bigcup_{Z \in U/Y} \underline{X}(Z)$. It is the object collection set which, according to the information of classification U/X, can be accurately allocated to the equivalence classes of Y. When $pos_X(Y) = pos_{X-\{x\}}(Y)$, x is regarded as unnecessary to Y in X, otherwise, x is regarded as essential. When each x is necessary to Y, then X is regarded as an independent to Y. If X' is the independent subset of X, and $pos_{X'}(Y) = pos_X(Y)$, then X' is called the reduction of X. The specific steps can be seen in reference [9].

D. Extraction of Reduced Decision Rules

Suppose attributes of the decision table $S = \langle U, R \rangle$ has been reduced. Let X_i, Y_j respectively represent the various equivalence classes of $U/X, U/Y$, $des(X_i)$: x_1 is s_1^i and x_2 is s_2^i, and x_m is s_m^i, $des(Y_j)$: y is s^j, respectively represents the description of the equivalence class X_i, Y_j, in which $s_k^i (k = 1,2,\cdots,m)$ is the value of attribute x_k, s^j is the value of attribute y. Decision rules are defined as: $R_{ij} : des(X_i) \rightarrow des(Y_j)$, $X_i \cap Y_j \neq \varnothing$, the strength of decision rules R_{ij} is defined as follows:

$$r_{ij} = \frac{|X_i \cap Y_j|}{|X_i|} \tag{5}$$

then

$$\Omega(S) = \{R_{ij} \mid i = 1,2,\cdots,|U/X|, j = 1,2,\cdots,|U/Y|, 0 < r_{ij} \leq 1\} \tag{6}$$

is called the rules set of S.

E. Fuzzy Neural Networks

The paper designs a four-layer feedforward neural network (see fig. 3), the first layer is the input layer, x_j represents the j_{th} component of input vector x, to which the j_{th} node corresponds. The component number of input vector x is the attribute number of the reduced decision table. The output is O_j^L, that is

$$I_j^1 = w_{sj} x_j, O_j^1 = I_j^1, j = 1,2,\cdots,n \tag{7}$$

The second layer is the membership function layer; it is used to calculate x_j's membership function of the linguistic variables fuzzy sets:

$$\mu_{A_{ij}}(x_j) = \exp\left[-\left((w_s x_j - w_c)/(1/w_d)\right)^2\right] \tag{8}$$

i is the fuzzy grade 3, w_s is the quantitative factor of the input variables, w_c is the central element of the membership function, w_d is the scale factor of the membership function, that is:

$$I_j^2 = O_n^1 - w_{cj}, \; O_j^2 = \exp\left[-\left(w_{dj} I_j^2\right)^2\right] \tag{9}$$

$j = 3(n-1)+1,\cdots,3n$.

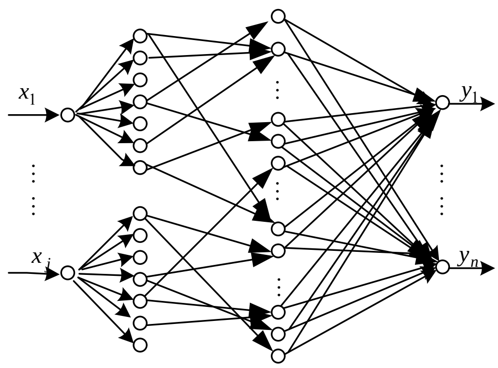

Figure 3. Fuzzy Neural Networks

The third layer is the rule layer, in which each node represents a rule. The access and description of rules is based on the rough set theory. The connection relations among the nodes of the third layer and that of the second and fourth layer are determined by the antecedent and the consequent. The nodes in the third layer complete their own fitness calculation. The output of the k_{th} node is

$$O_k^3 = O_{i_1}^2 O_{i_2}^2 \cdots O_{i_n}^2, \tag{10}$$

$O_{i_1}^2$, $O_{i_2}^2$, $O_{i_n}^2$ represent the output of the second layer nodes connected with the k_{th} node, $i_n = 3(n-1)+1,\cdots,3n$, $k = 1,2,\cdots,s$, s is the number of rules. The fourth layer is the output layer; and it plays the role of clarification, i.e. to obtain network output after defuzzification:

$$O_n^4 = \sum_k O_k^3 w_{bk} \tag{11}$$

The initial value of weight is preset to be the credibility value of each rule.

After the establishment of the network structure comes the learning phase. And the parameters of membership functions are to be optimized. Error function is defined as follows:

$$E=\frac{1}{2}\sum^{m}\left(y_0(t)-y(t)\right)^2 \qquad (12)$$

In the formula, m is the number of learning samples, $y_0(t)$ is the desired output value of the system, $y(t)$ is the actual output value of the system. Back-propagation thought is used to supervise the learning process. The error function E is minimized by adjusting the weights of the network, so as to achieve the purpose of correcting parameters of membership function. For each training data, starting from the input node, forward channel is used to calculate the activity level of each node in the network; starting from the output node, reverse channel is used to calculate $\frac{\partial E}{\partial y}$ of all hidden nodes. Suppose w is the adjustable parameter of a node, then the general learning rule is as follows:

$$\Delta w(t+1)=w(t)+\eta\left[-\frac{\partial E}{\partial w}\right], \qquad (13)$$

In which η is the learning rate. In order to represent the learning rules, starting from the output node, membership function is used to perform the calculation. Hence, the center w_{ci} and width w_{di} of the membership function are used as the adjustable parameters.

Suppose σ_j^L represents the error back-propagation signal of the j_{th} node in the L_{th} layer, then the error back-propagation signal of each layer is as follows:

The output layer:

$$w_{ci}=(t+1)=w_{ci}(t)+\eta[y_0(t)-y(t)]w_{di}O_i^4 \Big/ \sum_k w_{dk}O_k^4 \qquad (14)$$

$$w_{di}(t+1)=w_{di}(t)+\eta[y_0(t)-y(t)]\bullet\left[w_{ci}O_i^4\sum_k w_{ck}w_{dk}O_k^4-\right.$$

$$\left.\left[\sum_k w_{ck}w_{dk}O_k^4\right]O_i^4\right] \Big/ \left[\sum_k w_{dk}O_k^4\right]^2 \qquad (15)$$

The third layer:

$$\sigma_i^3(t)=[y_0(t)-y(t)]\left[w_{ci}O_i^3\sum_k w_{dk}\bullet O_k^3-\right.$$

$$\left.\left[\sum_k w_{ck}w_{dk}O_k^3\right]O_i^3\right] \Big/ \left[\sum_k w_{dk}\bullet O_k^3\right]^2 \qquad (16)$$

The second layer:

$$w_{cij(t+1)}=w_{cij}(t)-\eta\sum_k \sigma_k^3 O_i^2 2\left(O_i^1-w_{cij}\right) \Big/ w_{dij}^2 \qquad (17)$$

$$w_{dij}(t+1)=w_{dij}(t)-\eta\sum_k \sigma_k^3 O_i^2 2\left(O_i^1-w_{cij}\right)^2 \Big/ w_{di}^3 \qquad (18)$$

V. SIMULATION

To verify the validity of the proposed method, we design a REFNN model with 4 inputs and 6 outputs to detect maneuverable events of aircraft. Based on the sample data constructed in reference[15], a total of 380 samples are collected, 200 of which are training samples, and the rest are test samples. The input variables (condition attribute sets) are set to be the differences between the current state of target and that of the previous fusion cycle. They are: the height difference of the target location ΔH (rise is positive, decline is negative), the speed difference ΔV (increase is positive, reduction is negative), the horizontal angle of deviation from the original course $\Delta\alpha$ and the vertical angle of deviation from the original course $\Delta\beta$ (angle of clockwise and anticlockwise rotation has no effect on events detection , so the default value is set to be positive); the network input is represented by vector $x=\{x_1,x_2,x_3,x_4\}$; network output respectively represents the credibility of aircraft's climbing, accelerated climbing, hovering, horizontal steering, emergency steering, diving, etc. They are represented by vectors $y=\{y_1,y_2,\cdots,y_6\}$. When the network output credibility of a type of events is greater than the preset value k , the events are deemed to occur, k is usually set to be 0.65[10]. The desired output encoding of six types of events are e_1 (0.9, 0.1, 0.1, 0.1, 0.1, 0.1), e_2 （0.1, 0.9, 0.1, 0.1, 0.1, 0.1), e_3 (0.1, 0.1, 0.9, 0.1, 0.1, 0.1), e_4 (0.1, 0.1, 0.1, 0.9, 0.1, 0.1), e_5 (0.1, 0.1, 0.1, 0.1, 0.9, 0.1), e_6 (0.1, 0.1, 0.1, 0.1, 0.1, 0.9). The actual class is distinguished according to the maximal principle. The model is built by using the proposed method. Firstly, the sample data table is established, then GA algorithm is used to find the optimal discretization value of continuous attributes. And here are the parameters: initial population size is 20, P_s =0.7, P_c =0.65, P_m =0.05. The obtained optimal discretization values of continuous condition attributes are [5 5 4 3], and that of continuous decision attributes are respectively [3 4 3 5 4 3]. Based on the optimal discretization value of continuous attributes, we construct the corresponding decision table. Table I. is the discrete coding table of reduction attributes. ΔH , ΔV , $\Delta\alpha$, and $\Delta\beta$ are respectively represented by a,b,c,d , and are discretized into 5, 5, 4, 3.

TABLE I.
DISCRETE CODING TABLE OF REDUCTION ATTRIBUTES

		Attribute Value Coding				
Attribute Coding	Condition Attribute	0	1	2	3	4
a	ΔH	$(-\infty,-48)$	$[-48,-14)$	$[-14,23)$	$[23,48)$	$[48,+\infty)$
b	ΔV	$(-\infty,-16)$	$[-16,-2)$	$[-2,2)$	$[2,16)$	$[16,+\infty)$
c	$\Delta\alpha$	$[0,3)$	$[3,15)$	$[15,25)$	$[25,180)$	
d	$\Delta\beta$	$[0,5)$	$[5,20)$	$[30,180)$		

Table II. is a simplest decision table composed of 19 compatible rules. In this table, rule support is the degree of support of rules, which is determined by the ratio of the sample number represented by the rule itself to the total sample number of the type. Fuzzy neural network is constructed according to the rules of table 2. There are 4 nodes in the first layer which correspond to 4 condition attributes data. There are 12 nodes in the second layer which correspond to the membership functions of the linguistic variables fuzzy sets, to which each component belongs. The third layer has 19 nodes which correspond to 19 simplest decision rules. The fourth layer has 6 nodes which correspond to the six dynamic events of aircraft. The connection relations among the nerve cells in each layer can be determined according to the rules. When the fuzzy neural network is constructed, initialize the parameters which need to be adjusted. The values of membership function center w_{ci} and width w_{di} are assigned after estimating the training samples. The initial value of w_{bk} is assigned according to rule support (see table II). Train the BP network with 200 samples after its construction. In order to avoid over learning, training error precision is set to be 10^{-3}, the learning process is stable and convergent. The permissible error range is reached after 68 iterations. Refer to figure 4 for the BP network training error curve.

TABLE II.
SIMPLEST DECISION TABLE

Rule number	Rule	Rule Support	Rule number	Rule	Rule support
1	$a_3b_1c_0d_0 \to e_1$	0.76	11	$a_2b_1c_2d_0 \to e_4$	0.93
2	$a_2b_1c_0d_1 \to e_1$	0.90	12	$a_1b_3c_2d_1 \to e_4$	0.38
3	$a_2b_2c_1d_0 \to e_1$	0.82	13	$a_1b_1c_0d_1 \to e_4$	0.49
4	$a_2b_3c_2d_1 \to e_1$	0.24	14	$a_3b_4c_1d_0 \to e_5$	0.95
5	$a_3b_3c_0d_0 \to e_2$	0.79	15	$a_1b_1c_2d_0 \to e_5$	0.54
6	$a_3b_4c_1d_0 \to e_2$	0.93	16	$a_2b_3c_1d_0 \to e_5$	0.72
7	$a_2b_2c_0d_1 \to e_2$	0.49	17	$a_0b_2c_2d_0 \to e_6$	0.27
8	$a_2b_2c_1d_0 \to e_3$	0.81	18	$a_0b_4c_0d_2 \to e_6$	0.90
9	$a_1b_3c_2d_0 \to e_3$	0.34	19	$a_1b_3c_0d_2 \to e_6$	0.84
10	$a_3b_2c_0d_1 \to e_3$	0.21			

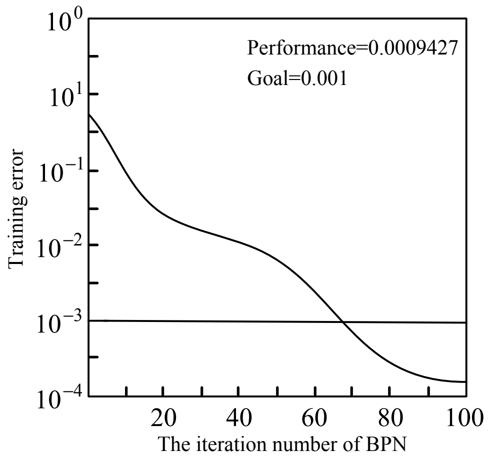

Figure 4. Training Error Curve of BPN

The same samples are sent to be trained in the IFNN proposed in reference[6], And the comparison of the two methods can be seen in table III.

As can be seen from Table III, the iteration number of network and rules of our proposed method are much less than IFNN, mainly because the proposed method use GA algorithm to find the optimal discretization degree of continuous attribute, and use rough sets to remove unimportant rules (the degree of support of rules is too low) , then acquire the minimal rule sets from data samples. Therefore, the construction of REFNN networks is much better than IFNN network in reference[6]. It took training time on GA and rough sets, And finnally the total training time of REFNN is 1.7 second less than that of IFNN. After network training, in order to compare the detection precision and real-time performance of the proposed method with FL(fuzzy logic) approach in reference [3] and IFNN in reference[6], use 180 test samples for testing, the test results shown in table IV.

TABLE III.
THE COMPARISON OF THE TWO METHODS

method	time（s）	iteration number of network	rule number
IFNN	16	392	48
REFNN	14.3	68	19

TABLE IV.
TH THE COMPARISON OF THE THREE METHODS

	Time(ms)	Error Rate	Omission Rate	Precision
FL	863	11%	5%	84%
IFNN	1074	6%	3%	91%
REFNN	962	3%	2%	95%

As is clearly shown in the experimental results, the real-time performance of the proposed method is better than IFNN, slightly worse than FL, but detection precision of the proposed method is much higher than other methods, FL method is only relatively effective to the simple event detection, complex maneuverable event detection precision is low.

V. CONCLUSION

In this paper, a method based on REFNN (Rough-Evolution Fuzzy Neural Network) is proposed to deal with such problems as imprecision and poor real-time performance in complex maneuverable events detection. Without expertise, the proposed method can sum up its own experience and extract rules from cases, hence, it's has higher intelligence and better real-time performance. In addition, using rough set theory to extract rules is especially suitable for information fusion in air combat because the rules extracted are partial ones, of which only some of the attributes are used and likewise, air combat information is often inaccurate and incomplete. As experiments have shown that the proposed method can reflect the good topology of data characteristics, it has simple structures and fast learning rate, hence, good feasibility.

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REFERENCES

[1] Emily W.Medina, Sunny Fugate, LorRaine. Next-Generation Tactical-Situation-Assessment Technology (TSAT) : Chat. ICWE 2007, LNCS 4607, p: 526–532.

[2] Rebecca Stewart. Neville A. Stanton. Don Harris etc. Distributed situation awareness in an Airborne Warning and Control System: application of novel ergonomics methodology. Cogn Tech Work(2008). 10:221–229.

[3] MA Yun, WANG Bao-shu, LI Wei-sheng. Situation awareness techniques in data fusion[J].Computer engineering, 2004, 30(1):85-87.

[4] LI Wei-sheng. Study of situation assessment techniques in information fusion system[D].Xi'an Electronic Science and Technology University, 2004.

[5] LEI Ying-jie, Wang Bao-shu, Wang Yi. Method of threat assessment based on intuitionistic fuzzy inference[J]. Journal of Electronics&Information Technology, 2007, 29(9):2077-2081.

[6] LIN Jian, LEI Ying-jie. Method of events detection based on intuitionistic fuzzy neural network[J]. Computer Engineering and Design, 2009, 30(6):1458-1460.

[7] LIU Dong, GU Zhi-yong, REN Bo, etc. Situation assessment of multi-aircraft cooperativeair combat in electronic countermeasure environment. Electronics Optics&Control, 2008, 15(7):30-33.

[8] ZHANG Dong-bo, WANG Yao-nan. Fuzzy-rough Neural Network and Its Application to Vowel Recognition[J]. Control and Decision, 2006, 21(2): 221-224.

[9] GAO Jian, TONG Ming-an .Extracting decision rules for cooperative team air combat based on rough set theory[J].Chinese Journal of Aeronautics, 2003, 16(4): 223-228.

[10] Zhang Dong-bo, Wang Yao-nan, and Yi Ling-zhi. Rough neural network and its application to intelligent information processing. Control and Decision, 2005, 20(2):121–126.

[11] Yu Chunyan, Wu Minghui, and Wu Ming. Combining rough set theory with neural network theory for pattern recognition. International Conference on Robotics, Intelligent Systems and Signal Processing, Changsha, 2003:880–885.

[12] Chen Shuang ye and Yi Jikai. A fuzzy neural network based on rough sets and its applications to chemical production process. Info-tech and Info-net, 2001. Proceedings, BeijingOct 29–Nov 1, 2001, 4:405–410.

[13] Wu Zhaocong. Research on remote sensing image classification using neural network based on rough sets. Info-tech and Info-net, 2001. Proceedings, Beijing Oct 29-Nov 1, 2001, 4:279–284.

[14] Yao Hong-xing, Zhao Lin-du, and Sheng Zhao-han. Application of multi-grade fuzzy neural networks in fault diagnosis of large machinery. Journal of Southeast University (Natural Science Edition), 2001, 31(2):59–63.

[15] CHEN Qi-shun. Calculation manual of aircraft Flight performance [M]. Beijing. Flight Mechanics journal press, 1987.

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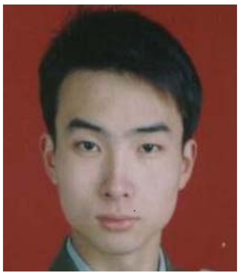

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