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An Expert System Reasoning Machine Based on the Combination of Fault Tree and Generalized Regression Neural Network

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***Abstract*—This paper is based on the background of the development of aviation fault diagnosis expert system. To solve the engineering problems of the low interpretation efficiency encountered in the construction of expert system, a reasoning machine based on the combination of Fault Tree (FT) and Generalized Regression Neural Network (GRNN) is brought forward. First, the FT model is built and simplified. Second, the FT model is transferred to Fault Dictionary (FD). And third, the GRNN model is built to learn the FD samples to achieve the rapid diagnostic reasoning of the complex FT logical criterion. Simulation shows that the GRNN model is better than the BP neural network model in the FD samples learning and has higher diagnosis accuracy. The reasoning machine is applied to the design of the aviation fault diagnosis expert system and improves the speed of reasoning.**

I. Introduction

Aviation fault diagnosis expert system mainly uses the computer automation to achieve the thought process of human experts which includes the observation and analysis of symptoms, the fault deduction and the disposal indication [1]-[2]. It can further improve the efficiency and accuracy of fault diagnosis, and reduce the false alarm rate, so that the technical staff can be liberated from the tedious work of data interpretation and rule inference, meanwhile, the experts can have more time to concentrate on the professional problems which really need their high level knowledge in the solving process. Aviation fault diagnosis expert system has high value of engineering application. This is also the inevitable trend of the development from manual work to half automation, and then to the automation, and then to the intelligence of the aviation fault diagnosis technology.

Reasoning machine is the core issue of aviation fault diagnosis expert system design. Its main function is to infer according to some reasoning methods by using the database of knowledge to achieve the requirements of fault diagnosis. The design of reasoning machine mainly considers two problems which include the reasoning control strategy and reasoning search strategy, which reflects the organization and control mechanism of aviation fault diagnosis expert system [3]. Generally, the scientificity and practicality of reasoning machine directly affect the feasibility and maturity of aviation fault diagnosis expert system.

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II. Related Works

The common reasoning methods used in the aviation fault diagnosis engineering are the logical reasoning methods based on Fault Tree (FT). The artificial deductive method is commonly used to establish a FT model. The logic rules derived from the FT model provide the criterions for fault detection and diagnosis. There are mainly three reasoning strategies: the first one is based on the FT graph and makes directly logical reasoning, which generally uses the Depth First Searching Algorithm and does inconvenient traversal search of each node in the logic tree [4]; the second one uses the logical inference rules derived from the FT model and makes query reasoning based on database, however, the database is a sparse matrix when the fault tree is huge, which needs long time query [5]-[6]; The last one combines both Fault tree and Neural Network, but some Neural Network models need empirical initial settings and cause no convergence phenomenon in the samples training, which affects the reasoning accuracy[7]-[9].

Aiming at above problems, this paper puts forward an expert system reasoning machine combined with Fault Tree (FT) and Generalized Regression Neural Network (GRNN). The GRNN model improves the reasoning speed of the complex FT logical criterion, needs less empirical initial settings and gets higher accuracy than BP neural network.

III. Reasoning Mechanism

A. Fault Tree Modeling

Fault tree is a special kind of inverted tree diagram which shows the logic relation of cause and effect, which is a logical, top-down, and step by step deductive analysis method in mathematics. The logical relationship is represented by a series of specific logic gates or symbols, which shows the interaction between system failure event and other events and intuitively describes how the failure event happened.

Artificial deductive method is commonly used to build a FT model. The general steps of fault tree modeling are shown in Figure 1.

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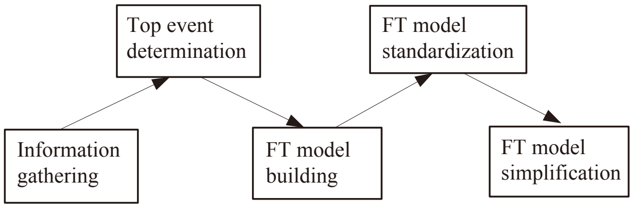

Fig. 1. Steps of FT modeling

The FT modeling process is simply described in following example of an aircraft undercarriage abnormal retracted failure:

(1) According to the fault phenomena and the state of the system, the "aircraft undercarriage abnormal retracted event" is determined as the top event. According to the working principle of aircraft undercarriage retracted mechanism, all the causes associated with the failure are investigated and listed.

(2) Take the top event *Top* as the first level of the fault tree. The direct cause *A* and *B* of the *Top* event are taken as the second level of the fault tree. Logic gates are used to connect the top event and the direct causes, according to the logical relationship between them.

(3) Gradually downward, the intermediate events *C* and *D* are taken as lower level events which cause event *A*, and the intermediate events *E* and *F* are taken as lower level events which cause event *B*.

(4) Events *G*, *H*, *I*, *J*, *K*, *L*, *M*, *N*, *O* are taken as the causes of events *C*, *D*, *E*, *F*, which are the bottom events of the fault tree.

Finally the FT model of aircraft undercarriage abnormal retracted event is established, which is shown in Figure 2.

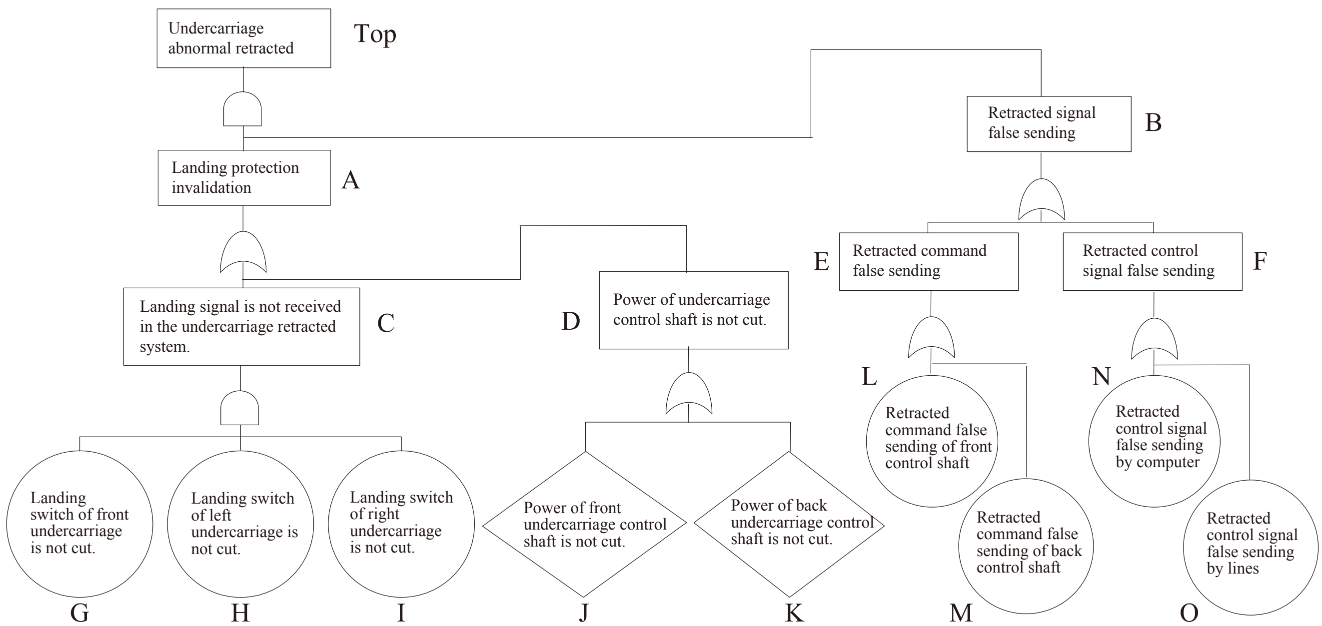

Fig. 2. Fault tree modeling of aircraft undercarriage abnormal retracted failure

B. Structure Function Simplification

The top event state of the fault tree is completely determined by the state of the bottom event, which has the following logical relations:

$$IF\ \ ((G\&\&H\&\&I)||(J||K))\&\&((L||M)||(N||O))\ \ THEN\ \ Top$$

The Structure Function of the fault tree can be established as follows:

$$Top = ((G \cdot H \cdot I) + (J + K)) \cdot ((L + M) + (N + O))$$

The above Structure Function is simplified:

$$Top = G \cdot H \cdot I \cdot L + G \cdot H \cdot I \cdot M + G \cdot H \cdot I \cdot N + G \cdot H \cdot I \cdot O +$$
$$+ J \cdot L + J \cdot M + J \cdot N + J \cdot O + K \cdot L + K \cdot M + K \cdot N + K \cdot O$$

Accordingly, it can be concluded that the original logical relationship which has both "&&" and "||" can be split into the following multiple simple logic relationships which only has "&&".

IF G&&H&&I&&L THEN Top
IF G&&H&&I&&M THEN Top
IF G&&H&&I&&N THEN Top
IF G&&H&&I&&O THEN Top
IF J&&L THEN Top
IF J&&M THEN Top
IF J&&N THEN Top
IF J&&O THEN Top
IF K&&L THEN Top
IF K&&M THEN Top
IF K&&N THEN Top
IF K&&O THEN Top

C. Generating Fault Dictionary

According to these simple logic relationships, the Fault Dictionary of aircraft undercarriage abnormal retracted failure can build as table 1.

TABLE I
FAULT DICTIONARY OF AIRCRAFT UNDERCARRIAGE ABNORMAL RETRACTED FAILURE

No.	Top	G	H	I	J	K	L	M	N	O
1	1	1	1	1	0	0	1	0	0	0
2	1	1	1	1	0	0	0	1	0	0
3	1	1	1	1	0	0	0	0	1	0
4	1	1	1	1	0	0	0	0	0	1
5	1	0	0	0	1	0	1	0	0	0
6	1	0	0	0	1	0	0	1	0	0
7	1	0	0	0	1	0	0	0	1	0
8	1	0	0	0	1	0	0	0	0	1
9	1	0	0	0	0	1	1	0	0	0
10	1	0	0	0	0	1	0	1	0	0
11	1	0	0	0	0	1	0	0	1	0
12	1	0	0	0	0	1	0	0	0	1

D. Learning Samples of GRNN

It is easy to see that the values of input event *G*, *H*, *I*, *J*, *K*, *L*, *M*, *N*, *O* and output event *Top* of Fault Dictionary can be either 0 or 1. The corresponding relationships between input event and output event in table 1 only constitute the 12 groups of learning samples whose outputs *Top* are all 1. These 12 samples can be called as fault samples. The normal samples with output 0 are still lacked, which is difficult to completely cover the correspondence between the input and output. Therefore, it is necessary to list all the input combination of events *G*, *H*, *I*, *J*, *K*, *L*, *M*, *N*, *O* corresponding to the output *Top*. Since the number of input events is 9, the total number of all the input event combination is $2^9=512$. The 512 samples construct all the learning samples of Neural Network. Among them, there are 12 kinds of input combination with output 1 shown in table 1 as fault samples. The remaining 500 kinds of input combination correspond to output 0 or output 1 according to the logic rules.

According to the Fault Dictionary, the input events *G*, *H*, *I*, *J*, *K*, *L*, *M*, *N*, *O* can be taken as the 9 inputs of GRNN. The output event *Top* can be taken as the output of GRNN. Thus, the GRNN model is built. Then, the 512 learning samples are sent to GRNN for learning.

IV. Simulations and Comparison

As we all know, different neural network models have different learning ability of the learning samples, which ultimately affects the ability of fault diagnosis. In the simulations, GRNN is compared with the BP neural network and the differences are analyzed.

(1) The BP neural network model was used to learn the 512 samples. The function in MATLAB is "newff". In the BP model, we chose 5 hidden layers, "logsig" function for hidden layers and output layer, "trainlm" as the training function, learning rate as 0.05, training precision as 0.001. The network learning curve obtained is shown in Figure 3. At that time, the trained BP network can do 511 correct diagnoses with 1 error diagnosis, whose fault diagnosis accuracy was 99.8%. It cannot further improve the accuracy of fault diagnosis by repeatedly adjusting the number of hidden layers, learning functions and training accuracy.

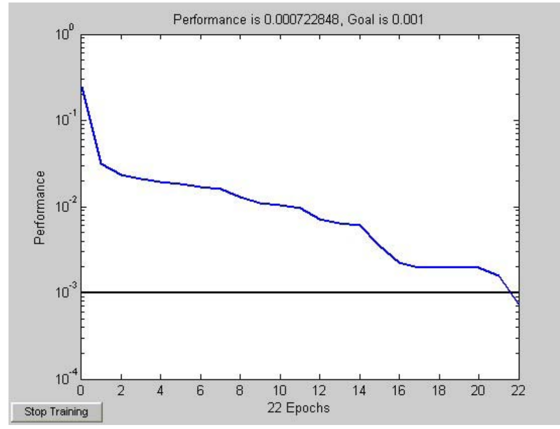

Fig. 3. The learning curve of BP neural network

(2) The GRNN model was used to learn the 512 samples. The function in MATLAB is "newgrnn".

We set spread parameter as 0.5. The trained GRNN can do 512 correct diagnoses with 0 error diagnosis, whose fault diagnosis accuracy was 100%.

Comparatively analyzing these two kinds of models, it can be concluded that, in the network samples learning of aircraft undercarriage abnormal retracted failure, GRNN shows better performance than BP neural network. The typical performances include:

(1) The network structure of GRNN is relatively simple. In addition to the input and output layers, it generally has only two hidden layers, without the need to estimate the number of hidden layers or the number of units in hidden layers. But the BP neural network needs to select the right number of hidden layers, the learning functions and so on.

(2) The network training of GRNN is very simple. When the training samples are transferred by the hidden layer, the network training is completed immediately at the same time. But the BP neural network often needs long time training and high computational cost.

(3) The result of GRNN has global convergence. While the calculation of standard BP neural network often cannot reach the global convergence and stop at local convergence.

Therefore, in the design of aviation fault diagnosis expert system, GRNN has better performance than BP neural network in learning the samples of Fault Dictionary. It has faster calculation process and higher diagnosis accuracy.

V. Conclusions

This paper presents an expert system reasoning machine based on the combination of Fault Tree (FT) and Generalized Regression Neural Network (GRNN). The complex fault tree logic reasoning is substituted by GRNN through the FT model simplification, transformation to Fault Dictionary, and the Fault Dictionary learning. In the implementation, the GRNN model can achieve better learning effect and higher diagnostic accuracy than BP neural network model, and needs less empirical initial settings. The reasoning machine has been applied to the design of aviation fault diagnosis expert system as the fault diagnosis module, which can be a reference for other expert system design. In fact, the reasoning machine not only can serve as the independent inference algorithm in aviation fault diagnosis expert system, but also can be combined with the aforementioned reasoning strategies such as fault tree figure reasoning, logic rule reasoning, etc. to improve the reliability and accuracy of the expert system reasoning.

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