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RESEARCH ON AERO-ENGINE VIBRATION FAULT BASED ON NEURAL NETWORK AND INFORMATION FUSION TECHNOLOGY

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Abstract: It is an important means for determining the conditions and making fault analysis of the aero-engine by measuring its vibration. Because the different features give different analysis results for vibration fault, in order to integration these information, the results of the different Back Propagation (BP) neural networks were fused by applying the Dempster-Shafer (D-S) evidential theory of the information fusion and the basic belief assignment function was established according to the statistical parameters of the networks. The analysis results from the aero-engine vibration signals show that the information fusion method can improve the reliability of the diagnosis and decrease the uncertainty.

Keywords: D-S evidence theory, Vibration, BP neural network, Aero-engine

1. INTRODUCTION

As the structure of the aero-engine becomes more and more complicated, especially for its high speed, high temperature and high pressure condition, the possibility of engine component failure will be greatly increased. The aero-engine condition monitoring and fault diagnosis system can improve significantly engine operating reliability and ensure flight safety. It is also for the realization of maintenance strategies from the regular maintenance to the status maintenance [1-2]. The shaft assembly of the aero-engine is the main object of detection and diagnosis, the main diagnostic method is vibration analysis. When measuring the vibration of aircraft engines, the sensors can only be installed in the engine casing outside, so the measured vibration signal contains different vibration excitation sources and a large number of measurement noise, it will bring vibration analysis more difficulties [3]. To realize accurate vibration analysis of aero-engine, it is necessary to apply information fusion technology. Through the fusion of multi-path diagnostic information, we can know and describe the diagnosis object more accurately and comprehensively.

D-S evidence theory has been widely used in fault diagnosis. This theory is first proposed by Dempster, and further developed by Shafer [4]. However, the DS evidence theory only gives the general algorithm of information fusion, it does not define the reliability function which directly affects the fusion result. There are still some difficulties in determining the reliability function when solving the fault diagnosis problem. In order to solve this problem, this paper proposes a method to construct the reliability function based on the actual working condition of the aero-engine, and uses the output of BP neural network to construct the relevant statistic parameters to obtain the reliability function. It is proved that the fault classification accuracy can be improved effectively by using fusion analysis.

2. THE BASIC DEFINITION AND SYNTHETIC RULES OF EVIDENCE THEORY

Set Θ as a finite set, N as a natural number, there are a total of N elements, then there are 2^N subsets in Θ, all pairs of elements in the set are mutually exclusive.

2.1 Basic probability assignment function

Set the function m : $2^\Theta \to [0,1]$, and satisfy $m(\Phi)=0$, $\sum_{A\subseteq\Theta} m(A)=1$, m is called the basic probability distribution function for 2^Θ, also known as the mass function. The basic probability distribution function of *A* reflects the degree of trustworthiness of *A*.

The mass function obtained by different information sources is not the same, which makes the evidence group for evidence fusion algorithm.

2.2The reliability function

If the function Bel : $2^\Theta \to [0,1]$, and satisfies:

$$Bel(A)=\sum_{B\subseteq A} m(B), \forall A \subseteq 2^\Theta \quad (1)$$

The function is called the reliability function. $Bel(A)$ is the degree of trust that *A* is true, it is the lower bound on the degree of trust *A*.

2.3 Joint Rules of Evidence

For the same identification framework, using different information sources derives the different mass function. Set $m_1, m_2, \cdots, m_n$ as the mass function in a recognition framework, the fusion of the mass function $m = m_1 \oplus m_2 \oplus \cdots \oplus m_n$ can be calculated by the following formula:

$$m(A)=K^{-1}\sum_{\cap A_j=A}\prod_{i=1}^{n} m_i(A_j) \qquad (2)$$

Where K is the conflict coefficient, and $K=\sum_{\cap A_j \neq \Phi} \prod_{i=1}^{n} m_i\left(A_j\right), j=1,2,\cdots,m$, which reflect the degree of conflict of the mass function.

The decision rule adopts the maximum trust rule, that is, the assumption with the largest probability of fusion is chosen as the decision result.

3. D-S FAULT DIAGNOSIS IMPLEMENTATION

The neural network can solve the complex nonlinear mapping from the fault symptom space to the fault space, so as to realize the fault diagnosis of aero-engine. But through the actual test and experience find that different fault features have different recognition ability for the fault mode. Therefore, this paper constructs an information fusion algorithm based on D-S evidence theory with different fault features to diagnose faults. The algorithm steps are:

(1) Firstly, the fault features are extracted by using different feature extraction algorithms for the aero-engine vibration dataset. Two features are used in this paper: sub-band energy feature of wavelet decomposition and entropy feature based on wavelet scale map, the specific algorithm can refer to the relevant literature [5-6];

(2) Input the extracted features into the corresponding trained BP neural network to diagnose and get the preliminary diagnosis results;

(3) The initial diagnosis results of each BP neural network are used as evidence, and all the failure modes are regarded as recognition frames. The final diagnostic results are obtained by D-S evidence theory.

The basic realization of the algorithm block diagram is shown in Figure 1.

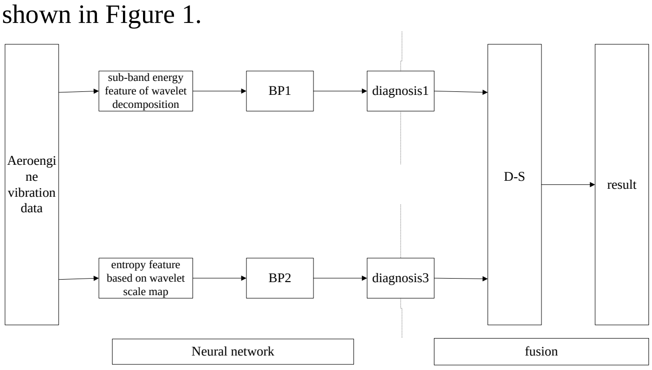

Fig.1 The basic realization of the algorithm block diagram

4. RELIABILITY FUNCTION CONSTRUCTION

The construction of the reliability function is the kernel problem of D-S evidence theory. In this section, we proposed a method to construct the reliability function according to the output of BP neural network.

We regard the elements contained in the evidence body E_i as an eigenvector $X_i=\left\{x_1, x_2, \cdots x_{N_i}\right\}$, where N_i is the length of the eigenvector. The standard eigenvector of the elements in the evidence body corresponding to the proposition in the framework F_j (the j^{th} fault) of standard eigenvector $Y_{ji}=\left\{y_1, y_2, \cdots y_{N_i}\right\}$. The distance between the unknown feature vector X_i and the standard feature vector Y_{ji} is:

$$d_{ij}\left(X_i, Y_{ji}\right)=\sqrt{\sum_{k=1}^{N_i}\left|x_k-y_k\right|^2} \tag{3}$$

As can be seen from the above formula, distance d_{ij} indicates the degree of proximity between the evidence body E_i and the framework F_j. The greater of the distance d_{ij}, the lower of the approach degree. According to the physical significance of the distance value, the correlation coefficient between the proof body E_i and framework F_j is as follows:

$$C_i\left(F_j\right)=1/d_{ij} \Big/ \sum_{j=1}^{M} 1/d_{ij} \tag{4}$$

Where M is the number of the fault in the framework.

According to the definition of relativity, the basic confidence distribution function $m_i\left(F_j\right)$ of the evidence body E_i and the uncertainty description $m_i(\theta)$ of the evidence body E_i can be obtained by the following formula:

$$m_i\left(F_j\right)=\frac{C_i\left(F_j\right)}{\sum_j C_i\left(F_j\right)+R_i} \tag{5}$$

$$m_i(\theta)=\frac{R_i}{\sum_j C_i\left(F_j\right)+R_i} \tag{6}$$

Where $R_i=1-w_i \cdot \alpha_i \cdot \exp(-\beta_i)$, represents the overall uncertainty of the diagnostic process.

w_i is the weight of the evidence body E_i. Because the evidence comes from different sources of information, the sensitivity and reliability of the failure to the information source are not the same. So, in the construction of basic probability distribution, w_i is used to improve the accuracy of decision-making.

$$\alpha_i=C_i\left(F_m\right)-\max_{j \neq m}\left\{C_i\left(F_j\right)\right\} \tag{7}$$

$$C_i\left(F_m\right)=\max_j\left\{C_i\left(F_j\right)\right\} \tag{8}$$

α_i is the difference of the correlation between the proof body E_i and framework F_j with the largest correlation coefficient and the second largest correlation coefficient, which reflects the degree of prominence of the proposition with the largest correlation coefficient in the recognition framework. The larger the value is, the more reliable the conclusion is.

$$\mu_i=\frac{1}{M-1} \sum_{\substack{j=1 \\ j \neq m}}^{M} C_i\left(F_j\right) \tag{9}$$

μ_i is the average of the correlation coefficients of the other propositions except the maximum correlation coefficient between the evidence body and each proposition.

$$\beta_i = \sqrt{\frac{1}{N-1}\sum_{\substack{j=1 \\ j\neq m}}^{M}\left(C_i\left(F_j\right)-\mu_i\right)^2} \qquad (10)$$

β_i is the mean square error of the correlation coefficient of the propositions except for the largest correlation coefficient in the evidence body and the recognition frame. This value reflects the degree of concentration of the correlation coefficients of the remaining propositions except for the proposition with the largest correlation coefficient in the recognition frame. The smaller the value that the more reliable the conclusion.

5. EXPERIMENTAL ANALYSIS

The vibration test database includes the rub data, imbalance data and the normal data of different working conditions for the aero-engine. Considering the richness of the noise in the collected signals, the wavelet soft threshold method is used to de-noise the signal before the feature extraction, so as to eliminate the large amount of interference components in the signal.

5.1 Performance under a single classification network

Firstly, the classification performance of each feature under its respective BP neural network is given. In the experiment, according to the vibration data obtained by the actual test, the total number of the normal signals is 260, the total number of the imbalanced signals is 102, and the total number of the rub signals is 164. During the training, about 80% of the feature data is randomly selected from the above set for network training, and the remaining features are used for network testing. According to the above analysis, the number of rub signals used in training is 131, the number of normal operating conditions data is 207, and the number of imbalanced signals is 79. So the number of rub signals in the test set is 33, the normal operating conditions is 53, and the number of imbalance signal features is 23. The BP neural network has 16 hidden nodes and the output contains 3 nodes. Among them, the output of imbalance fault is '100', the output of rub fault is '010', the output of normal condition is '001'. In order to present them in the figure, we can convert them to decimal numbers which correspond to ‘4’, ‘2’, and ‘1’, respectively.

Figure.2 and Figure.3 present the results of the classification based on the wavelet sub-band energy feature (BP network1) and wavelet entropy feature (BP network2), respectively. “∘”is the classification result of the network and “*” is its correct result. In the two figures, '4' corresponds to imbalanced fault, '2' corresponds to rub fault, '1' corresponds to normal operating condition. The results show that there are six misclassifications in the classification results based on the wavelet decomposition sub-band energy feature (from left to right, they are 14^{th}, 45^{th}, 46^{th}, 47^{th}, 49^{th}, 50^{th} features respectively in Figure 2), and six misclassifications are also found in the classification results based on the entropy feature of the wavelet scale graph (from left to right, they are 14^{th}, 35^{th}, 46^{th}, 61^{th}, 80^{th}, 81^{th} features respectively in Figure 3). The feature numbers of the misclassification are mostly different in the two features.

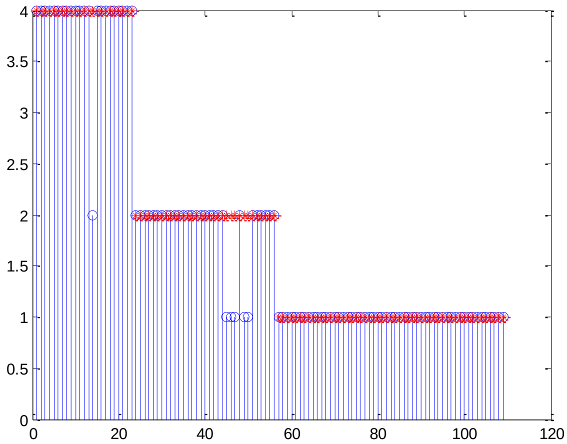

Fig2 The classification result based on wavelet decomposition sub-band energy feature

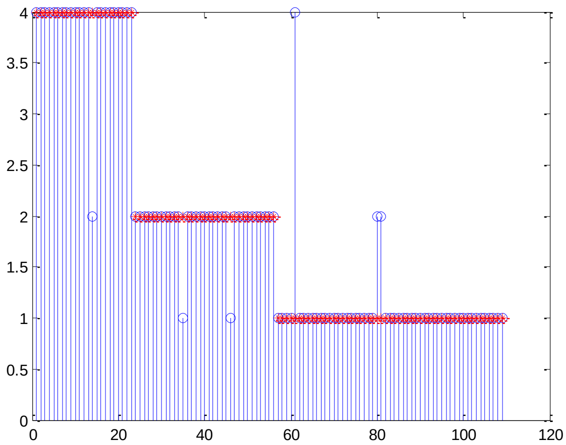

Fig3 The classification result based on entropy feature of the wavelet scale graph

5.2 Information fusion processing results

According to the definition form of the reliability function given above, the reliability function is calculated by the results of the two BP networks. After the D-S fusion, the new classification results are shown in Figure.4. It can be seen from the Figure4, the output for the imbalance has 1 error (the 14^{th}), rub has 2 errors (the 46^{th} and 50^{th}), and the normal operating conditions are classified correctly, there were only three classification errors. It can be seen that the number of total feature errors is decreased and the classification performance is improved compared with each sub-network classification.

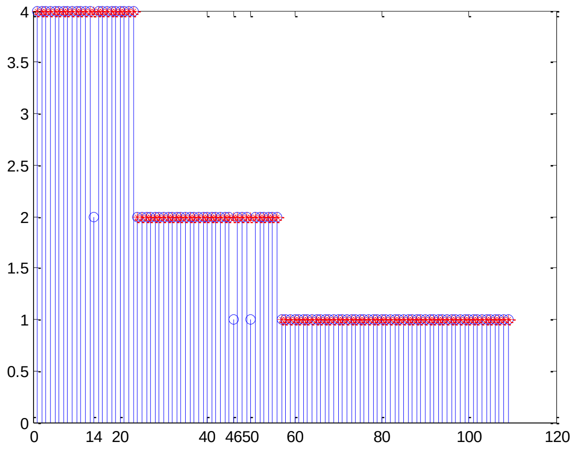

Fig4 The classification result based on D-S information fusion

The following is a detailed comparison of the characteristics of the data fusion.

First, for the completely correct classify data set, the change of the reliability function after the information fusion is observed. The results for the 11th data item are selected for analysis, it can be seen from Figure. 4 that the corresponding correct classification categories are imbalanced. Table 1 shows the corresponding sub-network and the fusion of the reliability function. From the table, we can see that after the fusion of network1 and network2, the reliability function of node 1 becomes larger, while the reliability function of other nodes become smaller and the degree of uncertainty decreases. This shows that the information fusion algorithm can further improve the reliability of classification, reduce the classification uncertainty and obtain more accurate classification results.

Table1 A Comparison of the Reliability Functions of Neural Networks under the 11th Data

	node 1	node 2	node 3	uncertainty	Result
BP1	0.7578	0.0408	0.0415	0.1599	imbalance
BP2	0.4361	0.1145	0.1005	0.3489	imbalance
1&2fusion	0.8388	0.0470	0.0438	0.0704	imbalance

Next, the data items for which the error is corrected are compared. Take the 80th data item as an example, we can see from Figure.4 that the corresponding correct category should be the normal. It can be seen from Figure. 2 that the classification result is correct in BP network1, and the classification results in BP network2 is wrong and it was recognized as rub fault. If the judgment of the maximum reliability function value of each sub-network node is independent, the correct classification result can not be determined. In particular, the network2 have large uncertainties. In order to judge the fault, the reliability function of each network and the results of fusion at each level are shown in Table 2. The information fusion between network1 and network2 can show that the error classification of network2 can be corrected after integration, and the maximum reliability function value appears on node 3. According to the maximum trust rule, the maximum value of the fused reliability function is chosen as the output result, so it has the maximum value on the node 3, and the fusion result is normal. As can be seen from the Table2, after the information fusion, we can correct the network2's errors, reduce the uncertainty of the entire classification, and get the correct classification results.

Table2 A Comparison of the Reliability Functions of Neural Networks under the 80th Data

	node 1	node 2	node 3	uncertainty	Result
BP1	0.0023	0.0023	0.9417	0.0538	normal
BP2	0.1533	0.3066	0.1102	0.4299	rub
1&2fusion	0.0169	0.0321	0.9101	0.0409	normal

Finally, it can also be seen from Figure 4 that for all sub-networks which are classified the wrong (such as the 14th data items), the information fusion algorithm can not get the correct results. This is because the information fusion algorithm itself is dependent on the output of each sub-network to achieve, if all sub-network errors, the final classification results must also be wrong.

6. CONCLUSION

Based on the actual vibration condition of aero-engine, this paper proposes a method to construct the reliability function under D-S evidence theory, and uses the fusion algorithm to fuse the diagnosis results under different BP networks. It realizes the analysis and diagnosis of the engine failure. Experimental results on aero-engine vibration data show that the DS evidence theory method has strong ability to deal with uncertain information, which can improve the reliability of diagnosis conclusion and reduce the uncertainty of diagnosis.

7. REFERENCES

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