Research on Fault Diagnosis of Complex Equipment Based on Artificial Intelligence

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Abstract: According to the requirement of fault diagnosis for complex equipment, the fault diagnosis signal is reconstructed by wavelet analysis technology and the multi-information fusion method of fault diagnosis based on evidence theory is established. The intelligent fault diagnosis method and fault reasoning method are established by using Bayesian network technology which provides the theory and method support for fault diagnosis of complex equipment.

1. Construct the fault diagnosis system for complex system
The fault diagnosis system for complex equipment uses the technology of intelligent information fusion and intelligent fault diagnosis, which is mainly composed of two functional modules: State Information Fusion and fault diagnosis, the Structure Diagram is shown in Figure 1.

2. Signal reconstruction of fault diagnosis based on wavelet analysis
Aiming at the determination of the external influence factors (noise, record error, information loss, etc.) of the fault signal of complex equipment, the wavelet transform is used to identify and reconstruct the abrupt change of the fault signal.
Let $\psi(t)$ be the basic wavelet, and its wavelet basis function can be obtained from $\psi(t)$

$$
\psi_{a,t}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-t}{a}\right)
$$

(1)

In the formula, $a > 0$, $t$ is the scaling factor, $\tau$ is the translation factor, and $1/\sqrt{a}$‘s function is to keep the wavelet basis functions have the same energy. Given the square integrable signal $x(t)$, or $x(t) \in L^2(R)$, the Continuous Wavelet Transform (CWT) of $x(t)$ is defined as

$$
WT_{x(t)}(a, \tau) = \int_{-\infty}^{\infty} x(t) \psi^*_{a,t}(t) dt = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^*\left(\frac{t-t}{a}\right) dt
$$

(2)

In the formula, $*$ denotes conjugation.

The inverse wavelet transform is given by the following Theorem:

Theorem 1, let $x(t), \psi(t) \in L^2(R)$, let $\Phi(\omega)$ be the Fourier transform of the wavelet $\psi(t)$, if the wavelet $\psi(t)$ satisfies

$$
c_{\psi} = \int_0^{\infty} |\Phi(\omega)|^2 d\omega < \infty
$$

(3)

Then $x(t)$ can be inversed by its wavelet transform $WT_{x(t)}(a, \tau)$, I. E

$$
x(t) = \frac{1}{c_{\psi}} \int_0^{\infty} \int_{-\infty}^{\infty} WT_{x(t)}(a, \tau) \psi_{a,t}(t) \frac{d\tau da}{a^2}
$$

$$
= \frac{1}{c_{\psi}} \int_0^{\infty} \int_{-\infty}^{\infty} WT_{x(t)}(a, \tau) \frac{1}{\sqrt{a}} \psi\left(\frac{t-t}{a}\right) \frac{d\tau da}{a^2}
$$

(4)

Formula (3) is called the admissibility condition of wavelets, from which it can be inferred that the basic wavelets should at least satisfy $\Phi'(\omega)|_{\omega=0} = 0$.

Wavelet transform is a multi-scale time-frequency analysis tool, which can describe the characteristics of data points effectively at small scale. With the increase of scale, wavelet transform has more and more obvious effect on signal smoothing (weighted average), at this time, the wavelet transform can show the trend of the data well. It is obvious that wavelet transform can describe local features such as data mutation and data trend mutation very well, and is very suitable for abnormal data recognition of equipment performance parameter samples.

3. Multi-information fusion of Fault diagnosis based on evidence theory

By using evidence theory to fuse multiple information of Health Monitoring, we can judge the reliability of relevant evidence according to the ambiguity and uncertainty of health monitoring signal, to determine the importance and reliability of the evidence from different sources, the data from multi-information fusion has higher reliability and accuracy, and provides more reliable data for fault diagnosis.

The basic probability assignment function (BPAF) $m:2^U \rightarrow [0,1]$ over $U$ is defined in evidence theory, which satisfies

$$
m(\Phi) = 0 \quad \sum_{A \subseteq U} m(A) = 1
$$

In the formula, proposition $A$ is a non-empty subset of $U$, and $M(A)$ reflects the reliability of $A$. 


If $K$ is the BPAF derived from $n$ independent evidences on the same recognition frame $U$, then the combination rule of Dempster is used to calculate the BPAF under the action of these independent evidences.

$$m(C) = \begin{cases} 0, & C = \emptyset \\ \frac{\sum_{A \in A} \prod_{i=1}^{n} m_i(A)}{1 - \sum_{\bigcap A \neq \emptyset} \prod_{i=1}^{n} m_i(A)}, & \forall C \subset U, C \neq \emptyset \end{cases}$$

How to make a decision after using evidence theory is a problem closely related to its application. The common decision-making methods include decision-making based on trust function, decision-making based on assignment of basic probability and decision-making based on minimum risk. Because the computation is small, the decision method based on the basic probability assignment is adopted here. Let $U$ be the identification frame. $M$ is the basic probability assignment based on Dempster combination rule. Assume \( \exists A_1, A_2 \subset U \), satisfy

$$m(A_1) = \max\{m(A_1), A_1 \subset U\}$$

$$m(A_2) = \max\{m(A_2), A_2 \subset U \text{and} A \neq A_1\}$$

if

$$m(A_1) - m(A_2) > \varepsilon_1$$

$$m(u) < \varepsilon_2$$

$$m(A_1) > m(U)$$

then $A_1$ is the verdict.

In the formula, $m(u)$ represents an unknown fundamental probability; $\varepsilon_1, \varepsilon_2$ is a predetermined threshold.

The multi-information fusion algorithm of equipment fault health monitoring based on evidence theory is based on multi-information monitoring and using Dempster combination rule, firstly, the attributes of health monitoring characteristic parameters are fused. Secondly, the time domain fusion of multiple monitoring cycles is carried out, and then the spatial domain fusion of multiple monitoring devices is carried out, and finally the fault source is identified.

4. Equipment Fault diagnosis based on Bayesian network

Bayes method can make a scientific judgment on the value of information or whether new information needs to be collected and make a quantitative evaluation on the possibility of the investigation results, skillfully combining prior knowledge with subjective probability, it can effectively analyze and diagnose the fault under complex condition.

The Bayesian network $\text{FBN}$, which is used to describe the fault state of complex systems, is based on the Bayesian Network, and uses fault events to constrain the semantics of nodes, edges and probability distributions. Fault Bayesian network is a binary group, \( \text{FBN} = (G_F, P_F) \), where $G_F$ is the topology of Fault Bayesian Network and $P_F$ is the probability distribution table of fault Bayesian network.

4.1 Bayesian network expression

Let $V$ be a set of random variables (containing $n$ finite variables), $G$ be a directed acyclic graph, $E$ be a directed edge set, $D$ be a conditional probability distribution set, and $P$ be a mathematical symbol of a Bayesian network. The MODEL is as follows:
Among them: 
\[ G = (V, E) \] 
\[ V = \{ V_1, V_2, ..., V_n \} \] 
\[ E = \{ V_i \mid V_j \} \] 
\[ P = \{ P(V_i | V_j) \} \]

4.2 Mathematical description of Bayesian network

Definition, Bayesian network is a fault diagnosis and maintenance decision model that expresses various information related to fault diagnosis and maintenance of equipment and their relationship using Bayesian network model. Using a Polygroup \(<v, D, P>\) to express,

In which: \( V = \{V1, V2, ..., V\} \); It is the node variable set that expresses the information related to fault diagnosis and maintenance decision in the network; \( D = V*V \); It is a directed edge set of connected nodes. \( P = \{P(V_i | V_j)\} \); It is a conditional probability table related to nodes in a network, expressing the strength of connections between nodes.

4.3 Construction of the Bayesian network

The first problem to be solved is how to realize the Bayesian network function of the system, which is based on the Bayesian network, the developed system must be able to assist the equipment maintenance experts to build a complete diagnosis model by accurate and convenient knowledge input according to the equipment design data, maintenance data and their own maintenance experience. Since the quality of the model will directly affect the accuracy of system reasoning and the efficiency of assistant decision-making, the primary task in the process of program design is to solve the problem of representation and storage of model knowledge, at the same time, it is necessary to design friendly man-machine interface and convenient knowledge input process to assist model building. The model knowledge acquisition process is divided as follows:

4.3.1 Defining network node variables

It includes the following contents: determining the classification of equipment fault symptoms, determining the possible fault causes related to fault symptoms, and the elements related to fault causes including observation, maintenance and related information and expressing them as node variables: determining the set of values of all node variables, the set should contain all possible values of the node variables, and there should be obvious repulsion and incompatibility between the different values; determine that the operation node contains the operation cost of observing and maintaining the operation node.

4.3.2 Construct a directed acyclic graph representing the relationships between node variables

In order to form the network structure of the diagnosis direction, the Directional Direction represents the process of fault location, and the system must ensure that the network structure is a directed acyclic graph, otherwise, it will directly affect the process of probabilistic reasoning.

5. Example analysis

The complex system consists of the following subsystems which is shown in Figure 2.
In the corresponding fault tree of the system, G12 is the top event, A, T, E, R, DP, SP, CD, BD1, BD2, B1 and B2 are the bottom events, G10, G1o, G40, G50, G11 and G12 are the intermediate events, the fault tree includes five logic gates a, b, c, e and g, two logic gates d and f. According to the mapping method from fault tree to fault Bayesian Network, the fault Bayesian network is obtained. The probability and conditional probability distribution of the corresponding nodes on the Bayesian network are shown in Table 1.

| Nodal point | Prior probability distribution | Nodal point | Prior probability distribution |
|-------------|-------------------------------|-------------|-------------------------------|
| T           | P(T)                          | BD2         | P(BD2)                        |
| A           | P(A)                          | B1          | P(B1)                         |
| E           | P(E)                          | B2          | P(B2)                         |
| R           | P(R)                          | G12         | P(G12/G11/G21/G50)            |
| G10         | P(G10/ATE)                    | G21         | P(G21/G10/G40)                |
| SP          | P(SP)                         | G11         | P(G11/RG10)                   |
| DP          | P(DP)                         | G50         | P(G50/B1/B2)                  |
| BD1         | P(BD1)                        | G30         | P(G30/SPDP)                   |
| CD          | P(CD)                         | G40         | P(G40/CDBD;BD2)               |

By means of structure transformation, belief initialization, belief transmission and absorption, the local calculation of fault probability provides a concise and scientific basis for fault diagnosis.

6. Conclusion
In this paper, a signal reconstruction model is proposed to remove the interference factors and process the signal data, which provides the basis for multi-information fusion. Aiming at the incompleteness and ambiguity of health monitoring information, a multi-information fusion method is established to process the information to meet the requirement of equipment fault diagnosis in complex environment. By using Bayesian network technology, this paper establishes the related concept model and mathematical model of fault diagnosis mode, improves the diagnosis method, and puts forward the utilization method of diagnosis result which provides reference for fault maintenance.

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