Mechatronics Fault Prediction and Diagnosis Based on Multi Sensor Information Fusion

Jinghua Yu*
Wuhan Institute of Shipbuilding Technology, Wuhan 430050 China

*Corresponding author: 26886003@qq.com

Abstract. This paper studies the mechatronics fault prediction and diagnosis based on multi-sensor information fusion. According to the method of data fusion, the fault diagnosis system is divided into data level fusion module, feature level fusion module and decision level fusion module. The data level fusion module mainly processes the measured signals of multi-sensor to extract the feature information of fault diagnosis. The feature level fusion module uses three parallel neural networks with the same structure. In this paper, the basic probability assignment method of decision level D-S evidence theory is used as the basic algorithm of data processing. The decision-making level uses the method of D-S evidence theory to fuse the results of feature level local diagnosis to get the final diagnosis result. The experimental data show that the accuracy and efficiency of the proposed Mechatronics fault prediction and diagnosis system based on multi-sensor information fusion can meet the requirements of engineering technology.

Keywords: Multi Sensor, Information Fusion, Fault Prediction, Fault Diagnosis.

1. Introduction
Multi sensor data fusion is a new technology developed in 1980s. It is based on multi-disciplinary theory, using computer technology, sensor technology, mathematical tools and signal processing technology to process data. Multi sensor data fusion technology was first applied in the military field, and has formed a relatively mature theory and method in IFF, track tracking, target positioning and other aspects. Data fusion technology shows its unique advantages [1-2].

Fault diagnosis is very important for the system with high security requirements. Timely detection of system faults can make the self repairing system reconstruct the control law in time, which can avoid system collapse and the resulting material losses and casualties. The model-based fault diagnosis method relies too much on the mathematical model of the system and is very sensitive to modeling error, parameter perturbation, noise and disturbance, which makes this method powerless for fault diagnosis of complex nonlinear systems. Neural network has the ability to approximate any complex nonlinear relationship and classification ability. The fault diagnosis of neural network has attracted the attention of scholars at home and abroad. In these neural network fault diagnosis methods, neural network classifiers usually face the problem of how to get decision functions with great generalization ability from limited fault samples.

At present, researchers fully exploit these advantages and apply the technology to industrial process
monitoring, industrial robots, air traffic control and other fields. Multi sensor data fusion technology develops with the development of different application fields and objects. At present, there is no specific and standardized unification of data fusion technology in various fields. The research on the application of this technology in fault diagnosis has been started in recent years. The research work in this area is still in its infancy, and has not formed a complete fusion system and theoretical framework of fault diagnosis [3]. The fusion diagnosis system in this paper applies multi-sensor data fusion technology to the field of fault diagnosis, and uses data fusion at different levels (or levels) to carry out fault diagnosis. The definition of multi-sensor data fusion fault diagnosis system can be summarized as: using multiple sensors to detect various physical quantities of the system from various aspects, grading multi-source information and data, accurately and timely judging the state of the system, giving the correct judgment of the system fault or not and fault mode. The relationship among state (fault), phenomenon (symptom) and cause is analyzed. The fault diagnosis system based on multi-sensor data fusion is called fusion diagnosis system for short.

2. Fusion diagnosis system

The main tasks of fault diagnosis are: fault detection, fault type judgment, fault location and fault recovery. Among them: fault detection is to periodically send detection signals to the lower computer after establishing the connection with the system, and judge whether the system has faults through the received response data frame; fault type judgment is to determine the type of system faults by analyzing the causes after the system detects faults; fault location is to refine the fault types and diagnose the faults on the basis of the first two parts Find out the specific fault location and cause of the system to prepare for fault recovery; fault recovery is the last and most important link in the whole process of fault diagnosis, and different measures need to be taken to recover the system fault according to the fault cause.

The system consists of three modules: data level fusion module, feature level parallel multi neural network local diagnosis module and decision level D-S evidence theory fusion diagnosis module. The structure of the system is shown in Figure 1.

![Figure 1 Architecture of fusion diagnosis system](image)

Support vector machine transforms the input space into a high-dimensional space through the nonlinear transformation defined by the inner product function, and finds the optimal classification surface in this space. SVM classification function is similar to a neural network in form. The output is a linear combination of intermediate nodes, and each intermediate node corresponds to a support vector. In view of the fact that support vector machine (SVM) can achieve the purpose of classification and generalization in the case of very small training samples, SVM is used as residual classifier to obtain the results of fault diagnosis. When there is no fault, the residual contains noise and unmodeled error; when there is fault, the residual deviates from zero in a specific way. After the residual error is generated, the fault detection and diagnosis information is obtained by SVM.

3. Each module of fusion diagnosis system

The data level fusion module is mainly used for multi-sensor data acquisition and feature extraction [4-6]. In order to carry out fault diagnosis, the main parameters needed are obtained from the test
bench through multi-sensor monitoring, and then converted into digital signals through D/A and A/D conversion, which are input to the computer for system monitoring and diagnosis. For vibration signal and thermal signal (such as temperature, pressure, etc.), the change speed is different, the former is faster, the latter is relatively slow. According to the difference of the two kinds of signals, two corresponding acquisition subsystems are used to collect the data respectively. The structure of the acquisition system is shown in Figure 2.

Figure 2 Data acquisition system structure

Measure the rotating speed with an eddy current sensor in the data acquisition system; Three eddy current sensors are used to measure the horizontal, vertical and axial vibration of the rotor. Two pressure transmitters are used to measure the pressure of oil manifold. The oil inlet temperature and oil return temperature are measured by thermal resistance. The vibration signal and rotation speed signal are converted into electrical signals by eddy current sensors. Since the converted electrical signals are analog signals, they need to be further converted into digital signals by the ADG404 high-speed signal acquisition board (A/D board) and input to the computer [7-8]. Temperature, pressure and other thermal signals are converted into analog electrical signals by transmitter, and then converted into RS485 standard signals by ADAM4017 data acquisition analog block. Since RS485 signals cannot be directly input into the computer, an ADAM4520 converter is needed to convert RS485 standard signals into RS232 standard signals, which are then input into the computer through the COM2 serial port of the computer.

For the parameters \((x_{i1}, x_{i2}, ..., x_{in})\) measured by the same kind of sensors, the average weighting method is used to fuse them, and the measured values close to the true values are obtained. The information \((x_1, x_2, ..., x_n)\) measured by different sensors is fused by least square method. After feature extraction, 30 feature quantities are obtained, which are divided into three categories: vibration parameters in time domain, vibration parameters in frequency domain and thermal quantities, as the input of feature level neural network. Because there are many features extracted here (mainly suitable for fault diagnosis of complex systems, because there are many abnormal parameters when faults occur in complex systems), there must be several important features for different faults, which play an important role in fault diagnosis. For example, for the two most common faults of steam turbine rotor, rotor mass unbalance and rotor misalignment, when rotor mass unbalance occurs, the characteristic of large amplitude corresponding to frequency doubling plays a decisive role in the fault. When the rotor misalignment occurs, the energy is mainly concentrated in the second harmonic generation, followed by the first harmonic generation and the third harmonic generation. The larger the energy difference between the second harmonic generation and the first harmonic generation, the more serious the rotor misalignment. Thus, these features are very important for the diagnosis of corresponding faults. Therefore, before the fault features are sent to the neural network, the weights of them are allocated. For those important parameters, they account for a larger proportion in the diagnosis of faults, and for those features which have a smaller role in the diagnosis of corresponding faults, they account for a
smaller proportion. In this way, the state of complex system can be fully reflected and the fault diagnosis is more accurate.

At the feature level, three parallel BP (back propagation) neural networks with the same structure are used. BP neural network is a mature neural network at present. The most basic three-layer BP algorithm is adopted here. The structure of the network is 10-21-5, and the error of the network is set at 0.005. The five outputs of the network are five common faults of steam turbine rotor: rotor mass unbalance, rotor misalignment, rotor rubbing, simultaneous occurrence of rotor mass unbalance and rotor misalignment, and oil whirl. BP network has two disadvantages: one is slow convergence; the other is easy to fall into local minimum. In this paper, the error of BP network is relatively large, it is not easy to fall into local minimum, and the learning and training speed is fast. Through the test, the average number of iterations of the three networks is 325, that is to achieve convergence, and the total learning and training time is 4.85s (the better the machine is configured, the shorter the learning and training time is).

4. Experimental investigation
The fusion diagnosis system is established by using the above theoretical methods, and the software is designed with Windows 98 as the development platform and Visual Basic 6.0 as the development tool. The diagnostic procedure is shown in Figure 3.

5. Diagnosis and conclusion
The diagnosis system is used to carry out on-line diagnosis on the turbine rotor test bench, and the diagnosis results are shown in Fig. 4 and Fig. 5 (the figure is a part of the computer interface, in order to make the diagnosis results clearer, a simple block diagram method is adopted).
The processing data obtained are shown in Table 1.

Table 1 Processing data

| Parameter | 0   | 0.2 | 0.4 | 0.6 | 0.8 | 1   | 1.2 | 1.4 | 1.6 | 1.8 | 2   |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| \( x_i \) (V) | 0   | 0.2 | 0.4 | 0.6 | 0.8 | 1   | 1.2 | 1.4 | 1.6 | 1.8 | 2   |
| \( y_i \) (μm) | 3.00 | 3.43 | 3.96 | 4.57 | 5.24 | 6.08 | 6.82 | 7.78 | 8.79 | 9.83 | 11.00 |
| \( y \) (μm) | 2.99 | 3.44 | 3.97 | 4.57 | 5.26 | 6.02 | 6.86 | 7.78 | 8.77 | 9.85 | 11.00 |
| \(|\Delta|\) (μm) | 0.01 | 0.01 | 0.01 | 0   | 0.02 | 0.06 | 0.04 | 0   | 0.02 | 0.02 | 0   |
| A (%)     | 0.33 | 0.29 | 0.25 | 0   | 0.38 | 0.99 | 0.59 | 0   | 0.23 | 0.20 | 0   |

6. Conclusion

It is more convenient to calculate the undetermined coefficient by using the algebraic formula derived in this paper. Then, the curve fitting is carried out, and the fitting accuracy is also very high, especially when the single-chip microcomputer is used for calibration. Therefore, it can be widely used in quadratic curve fitting in SCM calibration.

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